THE ACCOUNTING REVIEW

CUL-HC3047

VOLUME 83, No. 4 JULY 2008

uel
12/12/08

JOEL S. DEMSKI, HAIJIN LIN, and DAVID E. M. SAPPINGTON
Asset Revaluation Regulation with Multiple Information Sources

R. LYNN HANNAN, RANJANI KRISHNAN, and ANDREW H. NEWMAN
The Effects of Disseminating Relative Performance Feedback in Tournament and Individual Performance Compensation Plans

LESLIE HODDER, PATRICK E. HOPKINS, and DAVID A. WOOD
The Effects of Financial Statement and Informational Complexity on Analysts' Cash Flow Forecasts

KEVIN W. KOBELSKY, VERNON J. RICHARDSON, RODNEY E. SMITH, and ROBERT W. ZMUD
Determinants and Consequences of Firm Information Technology Budgets

KRISHNA R. KUMAR and GOPAL V. KRISHNAN
The Value-Relevance of Cash Flows and Accruals: The Role of Investment Opportunities

KARTIK RAMAN and HUSAYN SHAHRUR
Relationship-Specific Investments and Earnings Management: Evidence on Corporate Suppliers and Customers

FREDERICK W. RANKIN, STEVEN T. SCHWARTZ, and RICHARD A. YOUNG
The Effect of Honesty and Superior Authority on Budget Proposals

DAN WEISS, PRASAD A. NAIK, and CHIH-LING TSAI
Extracting Forward-Looking Information from Security Prices: A New Approach

YUE ZHANG
The Effects of Perceived Fairness and Communication on Honesty and Collusion in a Multi-Agent Setting

---

A JOURNAL OF THE
AMERICAN ACCOUNTING ASSOCIATION

AMERICAN ACCOUNTING ASSOCIATION

The members of the 2007–2008 Executive Committee of the Association are as follows:

President	Gary John Previts, Case Western Reserve University
President-Elect	Susan F. Haka, Michigan State University
Vice President	P. Jane Saly, University of St. Thomas
Vice President–Education	Philip M. J. Reckers, Arizona State University
Vice President–Finance	Joseph V. Carcello, The University of Tennessee
Vice President–International	Sidney J. Gray, University of Sydney
Vice President–Professional Relations	Bob Daugherty, PricewaterhouseCoopers
Vice President–Publications	David C. Burgstahler, University of Washington
Vice President–Research	Arnold M. Wright, Northeastern University
Vice President–Sections and Regions	Mark M. Higgins, University of Rhode Island
Past President	Shyam Sunder, Yale University

The American Accounting Association was founded in 1916 as the American Association of University Instructors in Accounting. Its present name was adopted in 1936. The Association is a voluntary organization of persons interested in accounting education, research, and practice. Full membership entitles one to receive *Accounting Education News*, a selection of one, two, or all three of the Association-wide journals (*The Accounting Review*, *Accounting Horizons*, and *Issues in Accounting Education*) and the opportunity to purchase Association publications at a discount.

Membership in the Association is available at the following annual rates:

Full membership:
The membership dues include online selection of one, two, or all three of the following Association-wide journals: *The Accounting Review*, *Accounting Horizons*, and *Issues in Accounting Education*. (This does not include Section journals.)

Select one Association-wide journal	U.S. $165.00	with Print Option $185.00
Select two Association-wide journals	U.S. $175.00	with Print Option $195.00
All three Association-wide journals	U.S. $185.00	with Print Option $205.00

Student membership:
The print option is not available for student members.

Select one Association-wide journal	U.S. $25.00
Select two Association-wide journals	U.S. $35.00
All three Association-wide journals	U.S. $45.00

In addition, full members may belong to one or more Sections: Accounting, Behavior and Organizations; Accounting Programs Leadership Group; American Taxation Association; Artificial Intelligence/Emerging Technologies; Auditing; Diversity; Financial Accounting and Reporting; Gender Issues and Worklife Balance; Government and Nonprofit; Information Systems; International Accounting; Management Accounting; Public Interest; Teaching, Learning and Curriculum; and Two-Year College. Each Section assesses its own annual dues, which are collected by the Association.

Editorial correspondence and all manuscripts should be emailed to tar@mccombs.utexas.edu or sent to Ms. Mary Capps, Editorial Assistant, *The Accounting Review*, The University of Texas at Austin, Department of Accounting, CBA 4M.202, 1 University Station B6400, Austin, TX 78712-0211.

The submission fee of $125.00 for members of the AAA or $200.00 for nonmembers should be paid online (VISA or MasterCard only) at: https://aaahq.org/AAAforms/journals/tarsubmit.cfm and must be paid when article is submitted. Request for reprint permission, subscriptions, advertisements, and dues should be sent to American Accounting Association, 5717 Bessie Drive, Sarasota, FL 34233-2399 • Telephone: (941) 921-7747 • Fax: (941) 923-4093 • Email: Office@aaahq.org. Notice of change of address should be mailed at least eight weeks in advance to ensure undelayed receipt of *The Accounting Review*.

The Accounting Review (ISSN 0001-4826 print and ISSN 1558-7967 online) is published six times a year in January, March, May, July, September, and November by the American Accounting Association, 5717 Bessie Drive, Sarasota, Florida 34233-2399. General subscriptions are available at the annual rates of $340 for a print copy or at $380 for a print and electronic copy. The member subscription rate for a hard-copy is $30. Electronic access is included with membership dues. Periodical postage paid at Sarasota, Florida and additional mailing offices. **POSTMASTER:** Send address change to *The Accounting Review*, 5717 Bessie Drive, Sarasota, Florida 34233-2399.

© 2008 American Accounting Association. All rights reserved. Printed in the United States of America.

THE ACCOUNTING REVIEW

A JOURNAL OF THE

AMERICAN ACCOUNTING ASSOCIATION

Senior Editor
Dan S. Dhaliwal
Editors
John E. Core
Steven J. Huddart
William Kinney
Marlys Gascho Lipe
William E. McCarthy
Mark W. Nelson
Madhav Rajan
Ad Hoc Editor
Paul E. Fischer

46

VOL. 83 JULY 2008 No. 4

JOEL S. DEMSKI, HAIJIN LIN, and DAVID E. M. SAPPINGTON
Asset Revaluation Regulation with Multiple Information Sources 869
R. LYNN HANNAN, RANJANI KRISHNAN, and ANDREW H. NEWMAN
The Effects of Disseminating Relative Performance Feedback in Tournament and Individual Performance Compensation Plans 893
LESLIE HODDER, PATRICK E. HOPKINS, and DAVID A. WOOD
The Effects of Financial Statement and Informational Complexity on Analysts' Cash Flow Forecasts 915
KEVIN W. KOBELSKY, VERNON J. RICHARDSON, RODNEY E. SMITH, and ROBERT W. ZMUD
Determinants and Consequences of Firm Information Technology Budgets 957
KRISHNA R. KUMAR and GOPAL V. KRISHNAN
The Value-Relevance of Cash Flows and Accruals: The Role of Investment Opportunities 997
KARTIK RAMAN and HUSAYN SHAHRUR
Relationship-Specific Investments and Earnings Management: Evidence on Corporate Suppliers and Customers 1041
FREDERICK W. RANKIN, STEVEN T. SCHWARTZ, and RICHARD A. YOUNG
The Effect of Honesty and Superior Authority on Budget Proposals 1083
DAN WEISS, PRASAD A. NAIK, and CHIH-LING TSAI
Extracting Forward-Looking Information from Security Prices: A New Approach 1101
YUE ZHANG
The Effects of Perceived Fairness and Communication on Honesty and Collusion in a Multi-Agent Setting 1125

BOOK REVIEW, Stephen A. Zeff, Editor

Christopher S. Chapman, Anthony G. Hopwood, and Michael D. Shields
Handbook of Management Accounting Research .... TOM GROOT 1147
Capsule Commentary .... STEPHEN A. ZEFF 1152
Editorial Data 1153
Editorial Policy and Style Information 1154

Editorial Staff of *The Accounting Review*
2007–2008

SENIOR EDITOR
Dan S. Dhaliwal, The University of Arizona and The University of Auckland

EDITORS
John E. Core
Steven J. Huddart
William Kinney
Marlys Gascho Lipe
William E. McCarthy
Mark W. Nelson
Madhav Rajan

AD HOC EDITOR
Paul E. Fischer

EDITORIAL ASSISTANT
Gail Emily Fey, The University of Arizona

P31444

American Accounting Association

EXECUTIVE DIRECTOR
Tracey E. Sutherland

COMMUNICATIONS DEPARTMENT
Beverly Harrelson
Diane Hazard
Lisa Habblitz
Kathy Casper
Judy Cothern
Deirdre Harris
Jan Kovarik (subcontractor)
Lorene Porte (subcontractor)
Anne Dempsey (subcontractor)

OTHER AAA STAFF
Debora Gardner
Peggy Turczyn
Barbara Brady
Pat Stein
Arlene Oliver
Kathleen Gwinn
Roland LaTulip
James Szelminski
Diane Leger
Man Fong
Kathleen McNeil

Editorial Advisory and Review Board

Shannon W. Anderson, Rice University
Anil Arya, The Ohio State University
Ramji Balakrishnan, The University of Iowa
Tim Baldenius, Columbia University
Orie E. Barron, The Pennsylvania State University
Sudipta Basu, Emory University
Anne L. Beatty, The Ohio State University
Daniel A. Bens, The University of Arizona
Jennifer Blouin, University of Pennsylvania
Robert J. Bloomfield, Cornell University
James R. Boatsman, Arizona State University
Christine A. Botosan, University of Utah
Mark T. Bradshaw, Harvard University
Brian J. Bushee, University of Pennsylvania
Jeffrey L. Callen, University of Toronto
William M. Cready, The University of Texas at Dallas
Patricia M. Dechow, University of Michigan and University of California, Berkeley
Mark L. DeFond, University of Southern California
Hemang Desai, Southern Methodist University
Ilia D. Dichev, University of Michigan
Sunil Dutta, University of California, Berkeley
Merle M. Erickson, The University of Chicago
Leslie G. Eldenburg, The University of Arizona
Paul E. Fischer, The Pennsylvania State University
Jennifer Francis, Duke University
Jere R. Francis, University of Missouri–Columbia
Jennifer J. Gaver, University of Georgia
Frank B. Gigler, University of Minnesota, Twin Cities Campus
Dan Givoly, The Pennsylvania State University
Cristi A. Gleason, The University of Iowa
Jonathan C. Glover, Carnegie Mellon University
Michelle Hanlon, University of Michigan
R. Lynn Hannan, Georgia State University
Rachel M. Hayes, University of Utah
D. Eric Hirst, The University of Texas at Austin
Frank D. Hodge, University of Washington
S. Paul Hribar, Cornell University
Christopher D. Ittner, University of Pennsylvania
Bruce W. Johnson, The University of Iowa
Karla M. Johnstone, University of Wisconsin–Madison
Kathryn Kadous, Emory University
Sanjay Kallapur, Purdue University and the Indiana School of Business
Steven J. Kachelmeier, The University of Texas at Austin
Bin Ke, The Pennsylvania State University
Elizabeth K. Keating, Harvard University
Inder K. Khurana, University of Missouri–Columbia
Ronald R. King, Washington University in St. Louis
April Klein, New York University
Lisa L. Koonce, The University of Texas at Austin
Ranjani Krishnan, Michigan State University
Linda K. Krull, The University of Texas at Austin
Christian Leuz, University of Pennsylvania
Carolyn B. Levine, Carnegie Mellon University
Robert Libby, Cornell University
Robert C. Lipe, University of Oklahoma
Oliver Zhen Li, University of Notre Dame
Laureen A. Maines, Indiana University
Carol A. Marquardt, New York University
Dawn A. Matsumoto, University of Washington
Edward L. Maydew, The University of North Carolina at Chapel Hill
Richard Mendenhall, University of Notre Dame
Michael B. Mikhail, Duke University
Gregory S. Miller, Harvard University
Lillian F. Mills, The University of Texas at Austin
Partha Mohanram, Columbia University
Donald Moser, University of Pittsburgh
James N. Myers, Texas A&M University
Venky Nagar, University of Michigan
Karen K. Nelson, Rice University
Kaye J. Newberry, University of Houston

Doron Nissim, Columbia University
Patricia C. O'Brien, University of Waterloo
Per M. Olsson, Duke University
Mark E. Peecher, University of Illinois at Urbana–Champaign
Kathy R. Petroni, Michigan State University
Morton Pincus, University of California, Irvine
Joseph D. Piotroski, The University of Chicago
Marlene A. Plumlee, University of Utah
Gordon S. Potter, Cornell University
Grace Pownall, Emory University
Suresh Radhakrishnan, The University of Texas at Dallas
Kannan Raghunandan, Florida International University
Shivaram Rajgopal, University of Washington
Scott A. Richardson, University of Pennsylvania
Darren T. Roulstone, The University of Chicago
Rachel Schwartz, University of Illinois at Urbana–Champaign
K. (Shiva) Sivaramakrishnan, University of Houston
Hollis Skaife, University of Wisconsin–Madison
Richard G. Sloan, University of Michigan
Geoffrey B. Sprinkle, Indiana University
Phillip C. Stocken, Dartmouth College
K. R. Subramanyam, University of Southern California
Hun-Tong Tan, Nanyang Technology University/Singapore
Robert H. Trezevant, University of Southern California
Mark Trombley, The University of Arizona
Mohan Venkatachalam, Duke University
Joseph P. Weber, Massachusetts Institute of Technology
Richard H. Willis, Tulane University
Peter D. Wysocki, Massachusetts Institute of Technology
Hong Xie, University of Illinois at Urbana–Champaign
Xiao-Jun Zhang, University of California, Berkeley

PAST EDITORS

1926–1929	William A. Paton	1973–1975	Thomas F. Keller
1929–1943	Eric L. Kohler	1976–1978	Don T. DeCoster
1944–1947	A. C. Littleton	1978–1983	Stephen A. Zeff
1948–1949	Robert L. Dixon	1983–1987	Gary L. Sundem
1950–1959	Frank P. Smith	1987–1990	William Kinney
1959–1962	Robert K. Mautz	1990–1994	A. Rashad Abdel-khalik
1962–1965	Lawrence L. Vance	1994–1997	Robert P. Magee
1965–1967	Wendell Trumbull	1997–2000	Gerald L. Salamon
1968–1970	Charles H. Griffin	2000–2002	Linda Smith Bamber
1971–1972	Eldon S. Hendriksen	2002–2005	Terry Shevlin

THE ACCOUNTING REVIEW
Vol. 83, No. 4
2008
pp. 869–891

American Accounting Association
DOI: 10.2308/accr.2008.83.4.869

Asset Revaluation Regulation with Multiple Information Sources

Joel S. Demski
University of Florida

Haijin Lin
University of Florida

David E. M. Sappington
University of Florida

ABSTRACT: We examine the design of asset revaluation policies in settings where a regulator can mandate fair value disclosure in order to mitigate a lemons problem in the asset resale market. The welfare-maximizing policy generally prescribes fair value certification for the lower asset values and (less costly) historical cost reporting for the higher asset values. The potential for voluntary certification can reduce welfare by increasing equilibrium certification costs and promoting underinvestment in socially valuable projects. Thus, a single regulated source of information (mandated disclosure) can be preferable to two sources of information (mandated and voluntary disclosure).

Keywords: *asset revaluation; certification; disclosure.*

I. INTRODUCTION

Many different asset revaluation rules are employed in practice. Common rules include lower of cost or market for inventory, net realizable value for receivables, and fair value for many financial instruments and impaired long-lived assets. The operation and impact of these revaluation rules are widely studied and fairly well understood. In contrast, relatively little is known about the conditions under which the various rules—together or in isolation—constitute optimal revaluation policies. This research derives the properties of optimal lower-tail

---

We thank Ron Dye, Hans Frimor, Bob Magee, Sri Sridhar, and seminar participants at Stanford University, Columbia University, Florida State University, Duke University, Northwestern University, The Ohio State University, University of Alberta, and the EIASM Workshop on Accounting and Economics for many helpful comments and suggestions. We are particularly grateful to the editor, Madhav Rajan, and two anonymous referees, whose suggestions have transformed and greatly improved our work.

Editor's note: This paper was accepted by Madhav Rajan.

Submitted: October 2006
Accepted: January 2008
Published Online: July 2008

asset revaluation policies in a simple, stylized setting and compares the optimal rules to the rules that are applied in practice.[1]

In our model, investors acquire private information about the value of projects in which they might invest. If a project is undertaken, then it is eventually sold in a resale market. A lemons problem (Akerlof 1970) arises in this resale market because potential buyers do not share the original investor's private information. The lemons problem produces an overinvestment distortion because investors undertake projects with negative expected net value, knowing that they ultimately can sell the resulting uncertified asset at a price that exceeds its true (expected) value.[2]

Symmetric knowledge of asset values can help to mitigate this lemons problem and the associated overinvestment distortion. Our model admits two potential sources of symmetric information: Mandated certification and voluntary certification. Mandated certification requires investors with the least valuable assets to certify the true value of their assets. When he knows that he will be required to reveal the true value of his asset, an investor will not pursue a project unless the value of the resulting asset exceeds its cost. Consequently, mandated certification reduces overinvestment by deterring investment in the least valuable projects.

Voluntary certification arises when investors certify the value of their assets even though they are not required to do so. Voluntary certification permits the owner of a high-value asset to sell the asset at a price that reflects its true (high) value rather than at a (lower) price that reflects the expected value of all uncertified assets. Voluntary disclosure of this type can provide useful information to asset buyers. However, it also can lead to underinvestment in socially valuable projects. The underinvestment arises when pervasive voluntary certification reduces the expected value, and thus the equilibrium price, of uncertified assets to the point where investors will only pursue projects if they ultimately plan to voluntarily certify the value of the resulting asset. Investors will not pursue projects with net values that are positive but less than the cost of voluntary certification under these circumstances, and so underinvestment occurs.

The optimal asset revaluation policy in this setting balances the costs of mandated asset revaluation against the corresponding benefits. The costs include both the institutional costs of establishing certification rules and processes and the additional costs associated with actually certifying the value of individual assets. The benefits of mandated revaluation include the mitigation of the lemons problem caused by asymmetric knowledge of asset values and the associated overinvestment distortion. Mandated certification also can reduce the extent of voluntary certification and thereby limit the associated certification costs and the underinvestment that voluntary certification can cause.[3]

Our analysis of optimal asset revaluation policies in this setting with two sources of information about asset values (mandated certification and voluntary certification) produces four primary findings. First, comprehensive fair value certification is an optimal asset revaluation policy only in the extreme setting where mandated certification is costless. Second, in more realistic settings where audited fair value disclosure is costly, the optimal revaluation rule prescribes fair value certification for the lower asset values and (less costly) historical cost reporting for the higher asset values. Third, when the cost of voluntary certification exceeds the cost of mandated certification, the optimal extent of mandated certification increases as the cost of voluntary certification declines. The increased incidence of mandated certification serves to limit the use of the more costly information source (voluntary certification) and to limit the underinvestment that voluntary certification can induce. Fourth, voluntary certification can reduce welfare by increasing equilibrium certification costs and promoting underinvestment in socially valuable projects. Thus, a single regulated source of information (mandated disclosure) can be preferable to two sources of information, one regulated and the other unregulated.

---

[1] Lower-tail asset revaluation policies mandate certification, i.e., fair value measurement, of the value of the least valuable assets. Such policies are common in practice, as illustrated by lower of cost or market for inventories or FAS No. 144 for long-lived assets.

[2] For expositional simplicity, we will often refer to "expected value" as "value" in the ensuing discussion.

[3] Mandated certification reduces voluntary certification by increasing the equilibrium price of uncertified assets and thereby reducing the private return to voluntary certification.

Our analysis of optimal asset revaluation policies proceeds as follows. Section II describes the key elements of our model. Section III characterizes the optimal asset revaluation policy in three benchmark settings: One where certification is costless; one where all forms of certification are prohibitively costly; and one where voluntary disclosure is the only source of information about asset values. Section IV identifies the optimal policy in the setting of primary interest—where both mandatory and voluntary certification are feasible—and explains how the potential for voluntary disclosure influences the optimal mandatory disclosure policy. Section V discusses extensions of our model and directions for further research.[4]

Before proceeding, we briefly relate our work to its predecessors. Our analysis may be most similar to Bachar et al.'s (1997) analysis in which a myopic, privately informed manager decides when to undertake costly asset certification. The authors compare the performance of lower of cost or market, fair value, and historical cost valuation rules. Our analysis differs by analyzing optimal asset revaluation policies, by focusing on the lemons problem in the market for assets rather than on problems caused by managerial myopia, and by considering the impact of revaluation requirements on investment and voluntary disclosure behavior.[5]

Our analysis of lower-tail disclosure rules links our work to the literature on asset write-down policies.[6] We extend this literature by emphasizing optimal lower-tail write-down policies, their interaction with voluntary disclosure, and their attendant investment distortions. We also contribute to the literature on voluntary disclosure (e.g., Dye 2001; Kanodia and Lee 1998; Verrecchia 1983, 2001) by emphasizing the interaction between regulation of financial reporting and the option to voluntarily disclose valuation-relevant private information.

II. THE MODEL

We consider a setting in which entrepreneurs choose whether to pursue investment projects that become available to them. We focus on the decision of a representative entrepreneur who can either undertake or decline to pursue a single investment opportunity. For example, the entrepreneur might be afforded the opportunity to create and then operate a small business venture.

To pursue the investment project (e.g., the small business venture), the entrepreneur must invest exactly $I > 0$ dollars. The ultimate payoff from this fixed investment is $\hat{x} + \mu + \varepsilon$, where $\hat{x}$ is the expected present value of the asset, and where μ and ε are the realizations of two independent random variables, $\tilde{\mu}$ and $\tilde{\varepsilon}$. The mean of each random variable is 0. For simplicity, $\tilde{\mu}$ is assumed to have a uniform distribution on the interval $[-f, +f]$. The entrepreneur observes the realized μ before deciding whether to invest the requisite I dollars or to refrain from investing. After observing the realized μ, the entrepreneur updates his expectation of the project's value from its *a priori* value ($\hat{x}$) to $\hat{x}+\mu$.[7]

---

[4] The proofs of all formal conclusions are provided in the Appendix.

[5] Our analysis is similar to Reis and Stocken's (2007) analysis in that both consider reporting of private information via a prescribed measurement rule (here a truncated version of fair value). While we limit strategic considerations to the investor's voluntary disclosure decision, Reis and Stocken (2007) analyze interactions among competing firms. Arya et al. (2007) also consider competitive interactions when examining the impacts of a requirement to report disaggregated demand information.

[6] See Alciatore et al. (1998), Dye (2001), and Verrecchia (2001), for example, for useful reviews of related investigations in this literature. Riedl's (2004) empirical analysis confirms the importance of opportunistic considerations in observed asset write-downs.

We assume the entrepreneur ultimately sells his investment project. Consequently, the entrepreneur's decision about whether to undertake the project and thereby develop a potentially valuable asset is influenced by the prevailing asset revaluation policy. The policy specifies when the entrepreneur must disclose the privileged information he has acquired about the value of his asset. Formally, the certification policy specifies the set of realized asset values ($\hat{x}+\mu$) that the investor must disclose.[8] Following institutional practice, we consider lower-tail certification policies, so the regulator specifies a critical asset value, $\hat{x}+\mu^m$, and requires the investor to certify the value of any asset that is below the specified critical value. To illustrate: If $\mu^m = 0$, then the investor must certify any asset value below its *a priori* value ($\hat{x}$); if $\mu^m = I - \hat{x}$, then the investor must certify any asset value below historical cost (I); and if $\mu^m \geq f$, then comprehensive fair value certification is required.[9]

For simplicity, we normalize to zero the cost of disclosing the historical cost of an asset. In contrast, additional disclosure of a realized asset value generally is costly. If the regulator imposes a nontrivial certification requirement (so $\mu^m \geq -f$), then the entrepreneur incurs a fixed cost, $K > 0$, if he undertakes the investment project, regardless of the expected value of the resulting asset (i.e., regardless of the actual realization of $\tilde{\mu}$). This cost can be viewed as a fixed, institutional cost associated with determining and being prepared to document accurately the value of the asset. In practice, these costs can include modeling, price tracking, and ensuring both the existence of an adequate audit trail and the infrastructure required to determine when revaluation is warranted.

Actual certification of an asset's value ($\leq \hat{x}+\mu^m$) requires an additional cost $k^m \geq 0$. In practice, these incremental certification costs can include payments to the valuation engineers or other consultants who perform the certification. These costs also might reflect expected litigation costs, which can arise even though the revaluation takes place under safe harbor provisions. All certification costs are borne by the investor, who is assumed to comply with the prevailing certification policy.[10] Both mandated and voluntary certification are assumed to reveal asset values accurately.[11]

Even if the entrepreneur is not required to certify the value of his asset (because this value exceeds the specified critical value, $\hat{x}+\mu^m$), he may choose to document a particularly high asset value in order to increase the sales price of the asset. For example, the small business owner who has discovered particularly lucrative opportunities for the business venture might document these opportunities in detail as a component of the certification process. The cost of such voluntary certification varies according to whether a nontrivial mandatory certification (MC) policy has been imposed. As noted, if a nontrivial MC requirement is in place, then the investor incurs institutional cost K, regardless of the realized value of his asset and regardless of whether he undertakes voluntary certification. Voluntary certification of any asset value above $\hat{x}+\mu^m$ then requires an additional cost $k^v \geq 0$.[12] If no substantive MC policy is in place, then voluntary certification (VC) entails cost $\bar{k}^v$. We do not restrict the value of $\bar{k}^v$ in most of the analysis. However, it is natural to think of $\bar{k}^v$ as being at least as great as $K+k^v$, in part because the standardized accounting and valuation procedures that are instituted as part of a nontrivial MC policy may provide safe harbor protection in the event of litigation.

---

[7] For example, the entrepreneur's careful study of the business opportunity might reveal pertinent, but still imperfect, information about the likely profitability of the business. The random variable $\tilde{\varepsilon}$ admits the realistic possibility that the investor is imperfectly informed about the value of his asset at the time he sells the asset. If the distribution of $\tilde{\varepsilon}$ were degenerate, then the lemons problem could be resolved trivially if investors could costlessly report the value of their assets and if a frictionless enforcement system were available to punish investors who misreport asset values.

[8] The entrepreneur who chooses to pursue his investment project will be referred to as "the investor."

[9] Thus, the class of policies that we analyze includes historical cost and fair value certification. The class also includes no mandated certification (such as expensing R&D expenditure) and conditional mandated certification (such as lower of cost or market). Policies that mandate the certification of selected high asset values without mandating the certification of low asset values could maximize expected welfare in settings where certification costs decline as asset values increase. However, such cost structures seem unlikely in practice for the reasons noted below.

[10] Thus, we abstract from considerations related to the enforcement of mandated certification policies. See Andreoni et al. (1998), Hope (2003), and Stocken (2000), for example, for analyses of enforcement issues in distinct but related settings.

[11] Some thoughts on imperfect certification are offered in the "Conclusions" section.

To ensure that the entrepreneur faces a meaningful investment decision, we maintain the following assumptions throughout the analysis:

Assumption 1: $\hat{x} > I + K$.
Assumption 2: $\hat{x} - f < I$.
Assumption 3: $\hat{x} + f > I + K + k^m$.

Assumption 1 implies that investment is profitable, on average, after accounting for the institutional costs of a nontrivial MC policy. Assumption 2 states that investment is not profitable for the lowest expected asset value ($\hat{x}-f$) even in the absence of certification costs. Assumption 3 indicates that investment is profitable for the highest expected asset value ($\hat{x}+f$), even after controlling for all of the costs associated with mandated certification of asset values. Together, Assumptions 1–3 imply that surplus is maximized if the project is undertaken for the highest expected asset values and not undertaken for the lowest expected asset values.

An optimal certification policy is one that maximizes the *ex ante* expected welfare of all market participants. Competition among asset buyers drives the equilibrium price of an asset to its expected value, given all information that is publicly available at the time the asset is sold. Consequently, asset buyers earn zero expected profit in equilibrium. Therefore, expected welfare is simply the entrepreneur's expected profit, which is the expected difference between the price at which he eventually sells his asset and the sum of his investment and certification costs.

An asset whose value has been certified (either by mandated or voluntary certification) is sold for a price equal to the certified value. An asset whose value has not been certified is sold at a price that reflects its expected value absent certification. This expected value is $\hat{x}+E\{\tilde{\mu} \mid \tilde{\mu} \in (\mu^m, \mu^v)\}$, where $\hat{x}+\mu^v$ is the smallest realized asset value for which the entrepreneur undertakes voluntary certification.[13] Thus, the price of an uncertified asset is a component of a perfect Bayesian equilibrium of a game in which: (1) all elements of the environment are common knowledge except the realization of $\tilde{\mu}$; and (2) asset buyers employ all available information to formulate their (Bayesian) beliefs about asset values before bidding the price of an asset down to the level of its expected value. If an uncertified asset is offered for sale when no such action should arise in equilibrium, then asset buyers believe the value of the uncertified asset is its *a priori* value ($\hat{x}$) plus a random draw from the support of $\tilde{\mu}$ where, in equilibrium, no investment should have occurred.[14]

Before proceeding, we briefly review the timing in the model. First, the regulator announces the certification policy (i.e., the critical asset value, $\hat{x}+\mu^m$, below which certification is required). Next, the entrepreneur acquires updated private information about the value of the asset that his project will produce, and decides whether to undertake the project. In the presence of a nontrivial mandatory certification policy ($\mu^m \geq -f$), the entrepreneur incurs cost K upon undertaking the project. Any incremental certification cost (either mandated or voluntary) is incurred before the asset is sold. The equilibrium price of the asset is then determined. Finally, the asset is sold.

---

[12] In parts of the ensuing analysis, we assume $k^v \geq k^m$ to account for the greater legal risk that can accompany claims of unusually high asset values in practice.

[13] Here and throughout the analysis, $E\{\cdot\}$ denotes the expectations operator.

[14] If investment (with certification) should have occurred for all $\tilde{\mu} \in [-f, f]$, then asset buyers believe the value of the uncertified asset is $\hat{x}-f$. The qualitative conclusions drawn below hold when alternative out-of-equilibrium beliefs are maintained. The key assumption is that out-of-equilibrium investment is believed most likely to have been undertaken by the entrepreneur when the value of his asset is relatively low.

III. BENCHMARK SETTINGS

Before proceeding to characterize the optimal asset revaluation policy in the setting of primary interest, we analyze the optimal policies and outcomes in three benchmark settings: (1) the *first best setting* in which all asset values are observed publicly at no cost; (2) the *no certification setting* in which no mandatory certification is imposed and voluntary certification is not feasible; and (3) the *no mandated certification setting* in which no mandatory certification is imposed but voluntary certification is feasible.

The First Best Setting

When certification of asset values is costless, the mandated certification (MC) policy that maximizes expected welfare entails comprehensive fair value reporting. This policy requires the (costless) certification of all asset values (so $\mu^m \geq f$). Under comprehensive fair value reporting, the asset is ultimately sold for a price that reflects its actual expected value ($\hat{x} + \mu$). Recognizing this fact, the entrepreneur only undertakes a project if its expected value exceeds the investment cost, i.e., if $\hat{x} + \mu \geq I$. Consequently, only projects with positive net value (i.e., those for which $\hat{x} + \mu \geq I$ or $\mu \geq I - \hat{x}$) are undertaken in equilibrium.

Because a comprehensive fair value mandate ensures that asset buyers share the investor's information about the value of his asset, expected welfare in the first best setting (W^{FB}) is simply the expected value of all projects with positive net value, i.e.:

$$W^{FB} = \int_{I-\hat{x}}^{f} [\hat{x} + \tilde{\mu} - I]\frac{d\tilde{\mu}}{2f} = \frac{1}{4f}[f - I + \hat{x}]^2.$$

The No Certification Setting

Now consider the opposite extreme where no information about the value of an asset other than its historical cost can ever be disclosed. A lemons problem (e.g., Akerlof 1970) arises in this no certification (NC) setting because the entrepreneur always has better information than asset buyers about the value of his asset at the time the asset is sold. The entrepreneur has no incentive to eschew projects with negative net value when all projects ultimately sell for the same price. Consequently, an equilibrium arises in the NC setting in which the entrepreneur always undertakes the project and the asset is ultimately sold at a price that reflects its *a priori* expected value ($\hat{x}$). Expected welfare in the NC setting (W^{NC}) is thus the difference between this price and the investment cost, i.e.:

$$W^{NC} = \hat{x} - I < W^{FB}.$$

Because the entrepreneur always undertakes the project in this equilibrium in the NC setting, overinvestment occurs relative to the first best level of investment, i.e., projects with negative expected net value ($\hat{x} + \mu - I < 0$) are undertaken.

The No Mandated Certification Setting

As a third benchmark, consider the setting where no mandatory certification (MC) is imposed and so voluntary certification (VC) is the only potential source of information about asset values (other than historical cost). In this no MC setting, investors with high-value assets will undertake VC if the cost of VC is less than the increase in the asset sale price it engenders. VC allows the investor to sell his asset at its expected value rather than at the (lower) equilibrium price of an uncertified asset. Thus, VC alone can help to resolve the lemons problem to some extent by distinguishing between (certified) assets with particularly high value and (uncertified) assets of lower value.

The extent to which VC mitigates the lemons problem and influences investment behavior depends upon the cost of VC. If VC is costless (so $\bar{k}^v = 0$), the first best outcome emerges as an equilibrium in the no MC setting. Anticipating (costless, voluntary) certification of the value of his asset, the entrepreneur will undertake the project only if its expected value exceeds its cost (so $\hat{x} + \mu \geq I$). A failure to undertake certification leads potential buyers to believe the value of the asset is less than its historical cost (I). Therefore, the entrepreneur would suffer a financial loss if he pursued a project with expected value below I.

As the cost of VC increases marginally above zero, investment continues to be profitable for the entrepreneur only if the value of his asset is ultimately certified (voluntarily) and thus only if the expected value of the project exceeds its cost. The cost of undertaking the project now includes both the investment cost (I) and the certification cost ($\bar{k}^v$). Consequently, underinvestment (relative to the first best investment level) arises because the entrepreneur will not pursue projects whose expected values are strictly positive but less than the cost of voluntary certification ($\bar{k}^v$). Although it induces underinvestment and (voluntary) certification costs, VC limits the lemons problem and avoids the associated overinvestment. On balance, when the stand-alone cost of VC is relatively small, VC increases expected welfare in the no MC setting above the level achieved in the no certification setting.

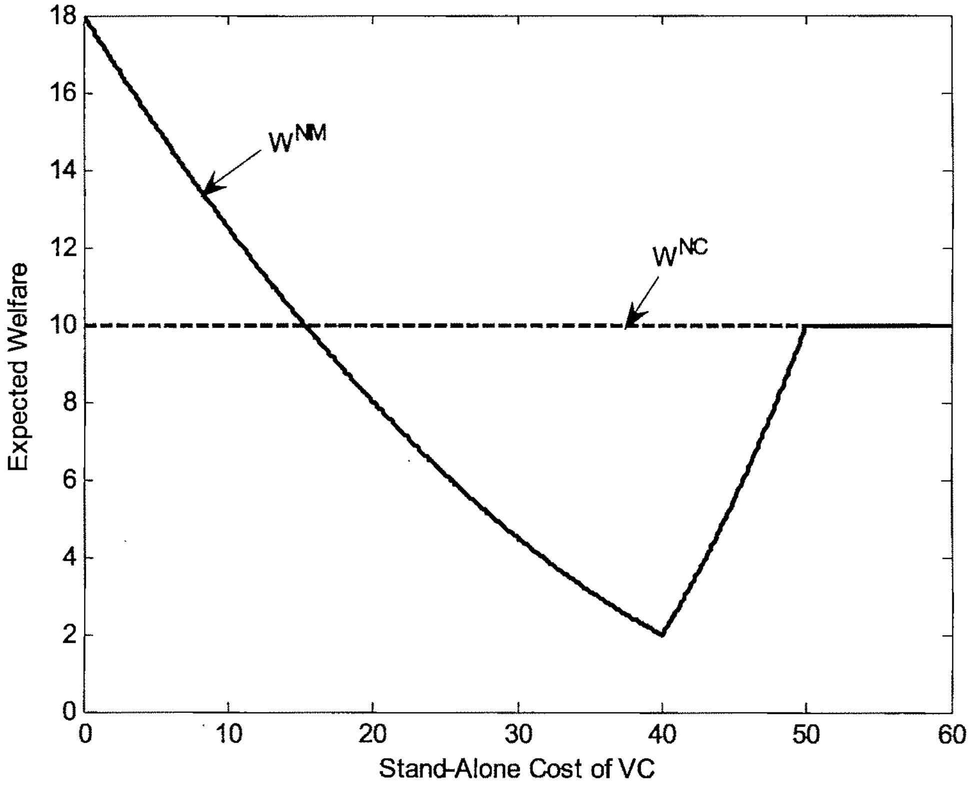
When VC becomes sufficiently costly, the investor will undertake VC in the benchmark no MC setting only if his asset is of such high value that certification would increase the sale price of the asset by more than the substantial certification cost, $\bar{k}^v$. When only projects with very high value are certified in equilibrium, many high-value assets are not certified and the expected value of all uncertified assets exceeds I, even when all potential investment projects are undertaken. Consequently, the entrepreneur will always find it profitable to undertake the project, anticipating voluntary certification if and only if the project is of exceptionally high value. Therefore, overinvestment emerges in the no MC setting when $\bar{k}^v$ is sufficiently large.

Because it allows the lemons problem to persist, induces overinvestment, and entails nontrivial certification costs, VC with moderately high certification costs reduces expected welfare (W^{NM}) in the no MC setting below the level achieved when neither mandated nor voluntary certification is possible (W^{NC}). Of course, when VC becomes sufficiently costly ($\bar{k}^v > f$), investors will never undertake VC in equilibrium and so the level of expected welfare in the no MC setting coincides with the level of expected welfare achieved in the NC setting (so $W^{NM} = W^{NC}$ when $\bar{k}^v > f$). These conclusions are recorded formally in Lemma 1.

Lemma 1: In the benchmark no MC setting, voluntary certification (VC) arises in equilibrium if and only if the stand-alone cost of VC is sufficiently small, i.e., if $\bar{k}^v \leq f$. When VC arises, it: (i) secures the first best outcome if $\bar{k}^v = 0$; (ii) induces underinvestment if $\bar{k}^v \in (0, f - \hat{x} + I)$; (iii) induces overinvestment if $\bar{k}^v \in [f - \hat{x} + I, f]$; (iv) increases expected welfare above W^{NC} if $\bar{k}^v < [\sqrt{f} - \sqrt{\hat{x} - I}]^2$; and (v) decreases expected welfare below W^{NC} if $\bar{k}^v \in [[\sqrt{f} - \sqrt{\hat{x} - I}]^2, f]$.

Figure 1 illustrates Conclusions (i), (iv), and (v) of Lemma 1 for the setting where $\hat{x} = f = 50$ and $I = 40$. As Conclusions (i) and (iv) indicate, when VC is the only source of information

FIGURE 1
Expected Welfare in the No Mandated Certification Setting (W^{NM}) and in the No Certification Setting (W^{NC}) versus the Stand-Alone Cost of Voluntary Certification ($\bar{k}^v$)



about asset values, VC increases expected welfare above W^{NC} when the cost of VC is sufficiently small ($\bar{k}^v \in (0\,,15.28)$).[15] In this case, VC is sufficiently pronounced in equilibrium that it eliminates the overinvestment caused by the lemons problem without inducing excessive certification costs. In contrast, as Conclusion (v) of Lemma 1 indicates, when VC becomes more costly (so $\bar{k}^v \in (15.28\,,50)$), its equilibrium incidence is so limited that the overinvestment problem remains and the relatively high certification cost reduces welfare below the level that would arise if no certification of any kind were feasible (W^{NC}).

In summary, voluntary certification can either increase or decrease welfare in the absence of mandatory certification. The same is true in the presence of mandatory certification, as the analysis in Section IV reveals.

---

[15] By design, historical cost is I regardless of asset value. Therefore, historical cost per se is uninformative about asset value. Notice that $[\sqrt{f} - \sqrt{\ell - I}]^2 = 15.28$ in the setting of Figure 1.

IV. THE OPTIMAL MANDATORY CERTIFICATION POLICY

Having determined the outcomes that would arise in the benchmark settings where mandatory certification is costless, where it alone is prohibitively costly, and where both mandatory and voluntary certification are prohibitively costly, we now analyze the optimal design of an asset revaluation policy under more realistic conditions. Our analysis of the optimal revaluation policy proceeds in two steps. First, we analyze the optimal policy when mandated certification is the only potential source of information (other than historical cost) about asset values. Then we analyze the optimal policy when voluntary certification also can provide information about asset values.

The Optimal MC Policy in the Absence of VC

To analyze the optimal asset revaluation policy in the absence of voluntary certification (VC), first consider the extreme case where the institutional costs of mandatory certification (MC) are zero (so $K = 0$). The regulator can secure the first best outcome in this case by requiring fair value reporting for all assets with expected value below investment cost I, and historical cost reporting otherwise. Formally, the optimal MC policy when $K = 0$ and VC is not feasible is to set $\hat{x} + \mu^m = I$ and thereby require the investor to certify any asset value that is below the investment cost. A project with expected value below I will not be profitable for the entrepreneur under this MC policy because, following certification, the asset will be sold at a price that reflects its expected value, which is less than I. Knowing that the certification policy has precluded investment in projects with value below cost, asset buyers will pay more than I for uncertified assets. Consequently, the entrepreneur will undertake the project if and only if its expected value exceeds I, which ensures the first best outcome.

The first best outcome is secured in this setting regardless of the incremental cost of mandated certification (k^m). No certification occurs in equilibrium because only low-value investments must be certified and these investments are deterred by the optimal MC policy. Therefore, expected welfare does not vary with the magnitude of k^m in this setting: In equilibrium all assets are measured at historical cost, and the first best level of expected welfare is achieved.

A trade-off emerges when the institutional costs of mandated certification are positive, as they are likely to be in practice. In this case, the regulator can continue to preclude low-value investments by requiring their certification. However, this requirement now entails a strictly positive certification cost for all asset values. This certification cost acts like a tax on investment. The tax induces underinvestment because the entrepreneur will decline to undertake a project for which certification will be required unless its expected value exceeds the sum of investment and certification costs (whereas first best investment entails investment whenever the value of an asset exceeds the investment cost, I).

As Proposition 1 reports, the optimal MC policy in this setting parallels the optimal policy in the first best setting (where $\hat{x} + \mu^m = I$) except that the cost of a project now reflects both the investment cost (I) and the institutional certification cost (K). Thus, the regulator optimally requires fair value reporting for all assets with value less than $I + K$ and historical cost reporting for all other assets. Of course, when the institutional certification costs are sufficiently large, the costs of mandated certification outweigh its benefits, and the regulator optimally requires only historical cost disclosure.

Proposition 1: Suppose voluntary certification is not feasible. Then the optimal asset revaluation policy imposes no certification mandate if and only if the institutional cost of mandatory certification (MC) is sufficiently large, i.e., $K \geq [\sqrt{f} - \sqrt{\hat{x} - I}]^2$. In this case, expected welfare under the optimal policy is $W^{NC} = \hat{x} - I$. In contrast, when $K < [\sqrt{f} - \sqrt{\hat{x} - I}]^2$, the optimal policy sets $\hat{x} + \mu^m$

$= I + K$ and secures expected welfare $\frac{[f - I + \hat{x} - K]^2}{4f} > W^{NC}$. This policy induces underinvestment whenever $K > 0$ and achieves the first best outcome only if $K = 0$.

Two additional elements of Proposition 1 warrant brief mention. First, the optimal MC policy is independent of the incremental mandated certification cost (k^m) because this cost is never incurred in equilibrium. The low-value projects for which certification ultimately would be required are never undertaken. All assets are measured at historical cost in equilibrium, and fair value measurement does not arise. Second, the critical level of institutional MC cost (K) above which MC reduces welfare in the absence of VC is precisely the stand-alone voluntary certification cost ($\bar{k}^v$) above which VC reduces welfare in the absence of MC (recall Lemma 1). The identical cutoffs arise because k^m is never incurred in equilibrium under the optimal MC policy when VC is prohibitively costly. Therefore, the relevant certification costs are K under MC and $\bar{k}^v$ under VC.

Proposition 2 next compares expected welfare under the two regimes that each entails a single source of information beyond historical cost: Either MC alone or VC alone. The proposition considers the case where certification costs are sufficiently small that: (1) some certification is mandated when VC is not feasible; (2) some voluntary certification arises in equilibrium in the absence of mandated certification; and (3) the least valuable projects are not undertaken in both settings.[16] The least valuable projects are not undertaken under the optimal MC policy because the policy mandates their certification, and thereby renders them unprofitable. The least valuable projects are not undertaken when VC is the only source of information about asset value other than historical cost because VC is sufficiently extensive as to reduce the equilibrium price of an uncertified asset below the associated investment cost, I.[17]

In the absence of voluntary certification in this setting, the optimal MC policy requires the investor to certify the value of any asset below $I + K$ (recall Proposition 1). The investor will not pursue such assets because their value (and thus their ultimate sale price) is less than the sum of their investment and certification costs. Thus, only assets with value above $I + K$ will be pursued, and none will be certified. The expected value of these assets, and thus their equilibrium price, is $P^{NV} = \frac{1}{2}[I + K] + \frac{1}{2}[\hat{x} + f]$, which reflects the average of the least and the most valuable uncertified assets that could arise in equilibrium. The investor's profit when his asset has value $\hat{x} + \mu \in [I + K, \hat{x} + f]$ in this setting is:

$$P^{NV} - [I + K] = \frac{1}{2}[\hat{x} + f - I - K]. \tag{1}$$

Consequently, expected welfare in this setting is:

$$W^{NV} = \frac{1}{4f}[\hat{x} + f - I - K]^2. \tag{2}$$

The welfare measure in Equation (2) is the product of the profit level specified in Equation (1) and the probability that the value of the investor's asset is at least $I + K$. This probability is $\frac{1}{2f}[\hat{x} + f - (I + K)]$.

In the absence of mandatory certification in this setting, only assets with value above the sum of investment costs and stand-alone certification costs ($I + \bar{k}^v$) will be developed, and the value of these assets will be certified voluntarily. The resulting level of expected welfare is the profit generated on each such asset $(\hat{x}+\mu-[I+\bar{k}^v])$, weighted by its likelihood, i.e.,

---

[16] As the proof of Proposition 2 reveals, this will be the case when $\max\{K, \bar{k}^v\} < [\sqrt{f} - \sqrt{\hat{x} - I}]^2$.

[17] The Appendix provides further explanation for this conclusion and the additional conclusions drawn in this section.

$$W^{NM}=\int_{I+\bar{k}^v-\hat{x}}^{f}[\hat{x}+\tilde{\mu}-(I+\bar{k}^v)]\frac{d\tilde{\mu}}{2f}=\frac{1}{4f}[\hat{x}+f-I-\bar{k}^v]^2. \tag{3}$$

The expressions in Equations (2) and (3) reveal that when only one information source is available (either MC or VC), the least costly information source generates the highest level of expected welfare. This conclusion is summarized formally in Proposition 2.

Proposition 2: Suppose $\max\{K,\bar{k}^v\}<[\sqrt{f}-\sqrt{\hat{x}-I}]^2$. Then $W^{NV}\gtreqless W^{NM}$ as $\bar{k}^v\gtreqless K$.

The Optimal MC Policy in the Presence of VC

We now consider the setting in which both mandatory and voluntary certification are feasible. Note, first, that if the cost of VC $(K+k^v)$ is sufficiently large, then investors will never voluntarily certify the value of their assets. Consequently, the optimal policy will be the policy described immediately above, where VC is not feasible.

More subtle considerations arise when VC is not prohibitively costly. In this case, the investor will undertake VC when his asset is of particularly high value in order to secure a higher price for the asset. When the most valuable assets are certified voluntarily, the equilibrium price of an uncertified asset declines, reflecting the lower expected value of an uncertified asset. The lower equilibrium price of an uncertified asset can induce the entrepreneur not to pursue the project when it has limited—but still strictly positive—value. To counteract this underinvestment problem, the regulator optimally imposes a fair value disclosure requirement for a broader set of the least valuable assets. The more extensive fair value disclosure requirement ensures that the least valuable assets are not offered for sale as uncertified assets, which increases the equilibrium price of an uncertified asset above I, ensuring that projects with positive net value are profitable even if they are not ultimately certified.

As Proposition 3 reports, when the incremental cost of VC exceeds the incremental cost of MC (so $k^v\geq k^m$), the regulator optimally extends the fair value disclosure requirement to the point where the price of an uncertified asset is sufficiently high that VC is no longer profitable for the investor.[18] Thus, the optimal MC policy reduces equilibrium certification costs by driving out the more costly information source, VC. Consequently, even though VC is feasible, it does not arise in equilibrium.

Proposition 3: Suppose $k^m\leq k^v\leq\frac{\hat{x}+f-I-K}{3}$ and $K+k^m<\min\{\bar{k}^v,[\sqrt{f}-\sqrt{\hat{x}-I}]^2\}$. Then the optimal asset revaluation policy entails nontrivial mandatory certification. Under the optimal MC policy: (i) investment is undertaken for all $\mu\geq\mu^*=I-\hat{x}+K+k^m$; (ii) mandated certification arises for $\mu\in[\mu^*,\mu^m]$, where $\mu^m=f-2k^v$; (iii) no voluntary certification arises; and (iv) expected welfare is $W^{MV}=\frac{[f+\hat{x}-I-K-k^m]^2}{4f}+\frac{k^v k^m}{f}$. The optimal policy requires comprehensive fair value reporting (so $\mu^m\geq f$) if and only if the incremental cost of mandatory certification (k^m) is zero.

Recall from Proposition 1 that when VC is prohibitively costly, certification of asset values below $I+K$ is optimally mandated (provided the institutional cost of certification, K, is not too large). Conclusion (ii) in Proposition 3 reports that when k^v is sufficiently small, this mandate is expanded to include all assets with value below $\hat{x} + f - 2k^v$.[19] Furthermore, the mandate increases at twice the rate that the incremental cost of voluntary certification declines (i.e., $\frac{\partial[\hat{x}+\mu^m]}{\partial k^v} = -2$). Given the presumed simple certification cost structure and the uniform distribution of $\tilde{\mu}$, this is the minimum rate at which the fair value reporting requirement must be expanded to make VC unprofitable for all asset values (as Conclusion (iii) indicates). This expansion of the fair value mandate enhances welfare both by eliminating equilibrium use of the more costly information source (voluntary certification) and by precluding investment in projects with negative value.[20]

---

[18] As noted above, the incremental cost of VC is likely to exceed the incremental cost of MC because of the greater legal risk that often accompanies claims of unusually high asset values.

Proposition 3 also reports that comprehensive fair value reporting is not optimal unless the incremental cost of mandated certification (k^m) is zero. When $k^m > 0$, the regulator can exempt the highest value assets from certification without inducing any VC, and thereby reduce equilibrium certification costs.

Proposition 3 considers a setting in which VC is more costly than MC (since $k^m \le k^v$ and $K + k^m < \bar{k}^v$). The regulator's ability to employ the less costly information source in this setting allows her to secure a higher level of expected welfare than would arise if no MC were possible (i.e., $W^{MV} > W^{NM}$). As Proposition 4 reports, though, the feasibility of VC generally is constraining, and so two potential sources of information are not always better than one. As explained above, the regulator optimally increases the critical asset value ($\hat{x} + \mu^m$) above the level she would implement if VC were not feasible in order to restore incentives to undertake investment projects with positive net value and to preclude equilibrium use of the more costly information source (VC). The resulting higher certification costs reduce expected welfare.[21] VC only fails to be constraining when the incremental cost of mandated certification (k^m) is 0 because the optimal MC policy entails comprehensive fair value reporting whether VC is feasible or infeasible in this case. Notice that fair value measurement arises in equilibrium here when $k^m > 0$ simply because the entrepreneur has the option to introduce another information source in the form of voluntary certification of asset value.

Proposition 4: Suppose $k^v \le \frac{\hat{x}+f-I-K}{3}$ and $K + k^m < \min\{\bar{k}^v, [\sqrt{f} - \sqrt{\hat{x} - I}]^2\}$. Then: (i) $W^{NV} > W^{MV} > W^{NM}$ when $k^m > 0$; and (ii) $W^{NV} = W^{MV} > W^{NM}$ when $k^m = 0$.

Before concluding, we note that the optimal asset revaluation policy precludes voluntary certification (VC) in equilibrium when VC is at least as costly as mandated certification (so $k^v \ge k^m$) because of the simple cost structure in our model. Both forms of certification can arise under an optimal asset revaluation policy more generally. To illustrate this point most simply while allowing for the possibility that certification costs might vary with asset value, suppose the incremental cost of mandatory certification (MC) increases linearly with asset value, so $k^m = \underline{k}^m + k_o^m[\hat{x} + \mu]$. Further suppose that: (1) the parameters $\underline{k}^m \ge 0$ and $k_o^m > 0$ are relatively small, so MC is not prohibitively costly and incremental MC costs do not increase too rapidly with asset value; and (2) k^v is intermediate in magnitude, and so exceeds k^m for small asset values but is less than k^m for large asset values.[22] The welfare-maximizing policy in this setting can be shown to mandate certification of asset values below $[k^v - \underline{k}^m] / k_o^m > 0$. This policy induces historical cost reporting for intermediate asset values and VC for the highest asset values. The equilibrium probability of MC decreases while the probability of VC increases as k_o^m increases, i.e., as incremental MC costs increase more rapidly with asset value. Thus, in general, MC, historical cost reporting, and VC all can arise in equilibrium under an optimal asset revaluation policy.[23]

---

[19] Notice that $\hat{x} + f - 2k^v > I + K$ (i.e., $k^v < [\hat{x} + f - I - K]/2$) in the setting of Proposition 1 since, by assumption, $k^v < [\hat{x} + f - I - K]/3$.

[20] It can be shown that when the institutional cost of certification is not too large (i.e., $K + k^v < \min\{\bar{k}^v, [\sqrt{f} - \sqrt{\hat{x} - I}]^2\}$) and the incremental cost of VC is less than the corresponding cost of MC (i.e., $k^v \le k^m \le \frac{\hat{x}+f-I-K}{3}$), then the optimal asset revaluation policy induces VC for all asset values above $I + K + 3k^v$, while no MC arises in equilibrium. Again, then, only the least costly information source is employed in equilibrium when certification costs do not vary with asset value.

[21] Of course, welfare rankings other than those reported in Proposition 4 can arise when different cost structures prevail. For example, if the stand-alone cost of VC ($\bar{k}^v$) is sufficiently small and is exceeded by the institutional cost of MC alone (K), expected welfare will be higher when certification is governed solely by the self-interested voluntary certification of investors than when nontrivial MC is imposed. Formally, it can be shown that if $k^v \le \frac{\hat{x}+f-I-K}{3}$, $k^m > 0$, and $\bar{k}^v < K < [\sqrt{f} - \sqrt{\hat{x} - I}]^2$, then $W^{NM} > W^{NV} > W^{MV}$.

V. CONCLUSIONS

We have examined the optimal design of lower-tail asset revaluation rules in a simple setting where asymmetric information creates a lemons problem in the asset resale market. An asset revaluation requirement (in effect, a fair value mandate) mitigates the lemons problem and the overinvestment it induces by rendering projects with negative net value unprofitable. Optimal asset revaluation rules balance these benefits against the costs of certification.

The optimal balancing of the benefits and costs of mandated certification varies with the ease with which an entrepreneur can voluntarily certify the value of his asset. When voluntary certification (VC) is not feasible, the optimal nontrivial mandatory certification (MC) rule requires fair value reporting for projects with negative net value. This requirement induces entrepreneurs to avoid such projects, and thereby eliminates the key lemons problem and the associated overinvestment. The requirement also ensures that only historical cost measurement arises in equilibrium. However, the institutional cost of MC acts like a tax on investment, and thereby produces underinvestment in equilibrium, as some projects with positive net value are not pursued.

The option to voluntarily certify asset values can complicate the design of the optimal MC policy by removing the most valuable assets from the set of uncertified assets, thereby reducing the equilibrium price of an uncertified asset. This price reduction can make it unprofitable to pursue a project with positive net value unless the value of the project is ultimately certified. To counteract this underinvestment problem created by VC, the optimal MC policy typically requires more extensive fair value reporting for the least valuable assets. Such expanded certification increases the equilibrium price of uncertified assets, and thereby reduces the profitability of VC. Thus, although VC can increase welfare when it is the only source of information about asset values, the presence of the VC option can reduce welfare below the level that can be achieved by an optimal MC policy when VC is not feasible.

Our model incorporated several simplifying features, including linear cost structures that defined the comparative advantage of the regulated and unregulated information sources. Alternative cost structures warrant consideration in order to ascertain the properties of optimal MC policies in more general settings.

We also did not allow the entrepreneur to acquire new private information about the value of his investment project after undertaking the project but before selling the resulting asset. This additional source of private information would allow asset write-downs to occur in equilibrium. Write-downs did not arise in our model because entrepreneurs decide not to pursue low-value projects at the outset under an optimal MC policy. If negative shocks to expected financial value were to arise after investment was undertaken but before the asset was sold, then optimal asset revaluation rules typically would entail some downward revision of disclosed asset values.

---

[22] Formally, suppose $\underline{k}^m < [\hat{x} + f - I - K]/3$, $k_o^m < \frac{\hat{x}+f-I-K-3\underline{k}^m}{\hat{x}+f+2[I+K]}$, and $k^v \in (k_L^v, k_H^v)$, where $k_L^v = [\underline{k}^m + k_o^m(I+K)]/[1-k_o^m]$ and $k_H^v = [\underline{k}^m + k_o^m(\hat{x}+f)]/[1+2k_o^m]$.

[23] As one further illustration of this more general point, suppose $\hat{x} = f = 50$, $I = 40$, $K = 5$, $k^v = 10$, and $\bar{k}^v = 15$. Also suppose the incremental cost of mandated certification (k^m) is 0 if $\mu \leq 0$ and $.16[\hat{x} + \mu]$ otherwise. It is readily verified that the optimal MC policy in this setting requires the certification of all asset values below 62.5. This policy induces no certification of asset values between 62.5 and 82.5, and historical cost measurement supplemented by voluntary disclosure for asset values above 82.5.

Our model also abstracted from any effort an entrepreneur might undertake to improve his knowledge of innate project value or to increase project value. Because asset revaluation rules can influence such efforts, it would be useful to analyze the optimal design of such rules in the presence of endogenous information about project values and endogenous project values.

Future research also might consider imperfect certification processes and incomplete compliance with certification mandates. Imperfect but unbiased certification would not seem to alter our primary qualitative conclusions because asset buyers are imperfectly informed about the value of a certified asset in our model whenever the distribution of $\tilde{\varepsilon}$ is nondegenerate. Therefore, additional uncertainty about the value of certified assets would not fundamentally alter our analysis. Of course, the optimal asset revaluation policy may mandate less certification when the information produced by the certification process is less accurate. When compliance with specified certification rules is not ensured, stochastic investigations of uncertified assets may be a component of an optimal certification policy. Increased reliance on voluntary certification also may be optimal.

Future research also might consider more general investment technologies. When more than two investment levels are feasible, an investor may attempt to signal the value of his project through the level of (observable) investment he undertakes. In this setting, the investment level joins mandatory and voluntary certification as potential sources of information about asset values. An investigation of the design of optimal asset revaluation rules in the presence of many information sources would be challenging, but instructive.

APPENDIX

PROOF OF LEMMA 1

When $\bar{k}^v < f - \hat{x} + I$, no uncertified assets are offered for sale and investment and voluntary certification are undertaken for all $\mu \geq \mu^v = I - \hat{x} + \bar{k}^v$, as:

$$\hat{x} + \mu - \bar{k}^v - I \geq \hat{x} + \mu^v - \bar{k}^v - I = 0.$$

If an uncertified asset were offered for sale, then the market would assume (employing the presumed out-of-equilibrium beliefs) that $\tilde{\mu}$ is uniformly distributed on $[-f, \mu^v]$. This implies a price of:

$$P = \hat{x} + \frac{1}{2}[\mu^v - f] = \hat{x} + \frac{1}{2}[I - \hat{x} + \bar{k}^v - f] = \frac{1}{2}[I + \hat{x} + \bar{k}^v - f] < \frac{1}{2}[I + \hat{x} + f - \hat{x} + I - f] = I. \quad \text{(A1)}$$

Because this price is less than investment cost I, the entrepreneur would not pursue the investment project when $\mu < \mu^v$. Consequently, expected welfare in this case is:

$$\begin{aligned} W^{NM} &= \int_{\mu^v}^{f} [\hat{x} + \tilde{\mu} - I - \bar{k}^v] \frac{d\tilde{\mu}}{2f} \\ &= \frac{[\hat{x} - I - \bar{k}^v][f - \mu^v]}{2f} + \frac{[f^2 - (\mu^v)^2]}{4f} \\ &= \frac{1}{4f}[f - \mu^v][2\hat{x} - 2I - 2\bar{k}^v + f + \mu^v] \end{aligned}$$

$$= \frac{[f + \hat{x} - I - \bar{k}^v]^2}{4f}. \tag{A2}$$

From (A2), $W^{NM} = W^{FB}$ when $\bar{k}^v = 0$.

When $\bar{k}^v \in [f - \hat{x} + I, f]$, entrepreneur invests for all realizations of $\tilde{\mu}$. In equilibrium, μ^v is determined by:

$$\hat{x} + \mu^v - \bar{k}^v = P, \quad \text{or } \mu^v = P + \bar{k}^v - \hat{x}, \tag{A3}$$

and the price of an uncertified asset is:

$$P = \hat{x} + \frac{1}{2}[\mu^v - f] = \hat{x} + \frac{1}{2}[P - \hat{x} + \bar{k}^v - f]. \tag{A4}$$

(A3) and (A4) imply:

$$P = \hat{x} + \bar{k}^v - f \geq \hat{x} + f - \hat{x} + I - f = I. \tag{A5}$$

Substituting the expression for P in (A5) into (A3) provides:

$$\mu^v = \hat{x} + \bar{k}^v - f + \bar{k}^v - \hat{x} = 2\bar{k}^v - f \leq 2f - f = f. \tag{A6}$$

Expected welfare in this case is:

$$\begin{aligned} W^{NM} &= \int_{-f}^{\mu^v} [P - I]\frac{d\tilde{\mu}}{2f} + \int_{\mu^v}^{f} [\hat{x} + \tilde{\mu} - I - \bar{k}^v]\frac{d\tilde{\mu}}{2f} \\ &= \frac{1}{2f}[P - I][\mu^v + f] + \frac{1}{2f}[\hat{x} - I - \bar{k}^v][f - \mu^v] + \frac{1}{4f}[f^2 - (\mu^v)^2] \\ &= \frac{1}{2f}[\hat{x} + \bar{k}^v - f - I][2\bar{k}^v] + \frac{1}{2f}[\hat{x} - I - \bar{k}^v][2f - 2\bar{k}^v] + \frac{1}{4f}[f^2 - (2\bar{k}^v - f)^2] \\ &= \frac{\bar{k}^v}{f}[\hat{x} - I] + \frac{1}{f}[\hat{x} - I - \bar{k}^v][f - \bar{k}^v] \\ &= \hat{x} - I - \bar{k}^v + \frac{(\bar{k}^v)^2}{f}. \end{aligned} \tag{A7}$$

When $\bar{k}^v > f$, no VC arises in equilibrium because (A6) implies:

$$\mu^v = 2\bar{k}^v - f > 2f - f = f.$$

The entrepreneur will always invest and sell his uncertified asset in this case at price $P = \hat{x}$. Expected welfare will be:

$$W^{NM} = \hat{x} - I. \tag{A8}$$

(A2) implies that when $\bar{k}^v < f - \hat{x} + I$, the difference between expected welfare in the presence of VC and in its absence (in which case expected welfare is W^{NC}) is:

$$
\begin{aligned}
G(\bar{k}^v) &\equiv \frac{[f - I - \bar{k}^v + \hat{x}]^2}{4f} - [\hat{x} - I] \\
&= \frac{1}{4f}\{[f - \bar{k}^v]^2 + [\hat{x} - I]^2 + 2[f - \bar{k}^v][\hat{x} - I] - 4f[\hat{x} - I]\} \\
&= \frac{1}{4f}\{[f - \bar{k}^v]^2 + [\hat{x} - I]^2 - 2[f + \bar{k}^v][\hat{x} - I]\} \\
&= \frac{1}{4f}\{[f + I - \hat{x} + \bar{k}^v]^2 - 4f\bar{k}^v\}. \qquad \text{(A9)}
\end{aligned}
$$

(A9) implies $G'(\bar{k}^v) = \frac{1}{2f}[-f + I - \hat{x} + \bar{k}^v] < 0$ when $\bar{k}^v < f - \hat{x} + I$. Also, $G(\bar{k}^v) > 0$ for $\bar{k}^v < [\sqrt{f} - \sqrt{\hat{x} - I}]^2$, while $G(\bar{k}^v) \leq 0$ for $\bar{k}^v \in [[\sqrt{f} - \sqrt{\hat{x} - I}]^2,\ f - \hat{x} + I)$. In addition, Assumption 2 ensures $[\sqrt{f} - \sqrt{\hat{x} - I}]^2 < f - \hat{x} + I$.

From (A7), the difference between expected welfare in the presence of VC and in its absence when $\bar{k}^v \in [f - \hat{x} + I, f]$ is:

$$H(\bar{k}^v) = \hat{x} - I - \bar{k}^v + \frac{(\bar{k}^v)^2}{f} - [\hat{x} - I] = -\bar{k}^v + \frac{(\bar{k}^v)^2}{f} = \frac{\bar{k}^v[\bar{k}^v - f]}{f} \leq 0. \qquad \text{(A10)}$$

■

PROOF OF PROPOSITION 1

When a nontrivial MC policy is imposed, it is as if the investment cost is increased from I to $I + K$. Since expected welfare in the first best setting is $W^{FB} = \frac{1}{4f}[f + \hat{x} - I]^2$, imposing MC cannot achieve a welfare measure that exceeds $\frac{1}{4f}[f + \hat{x} - I - K]^2$. An MC policy of $\mu^m = I - \hat{x} + K$ achieves precisely this welfare measure and thus is optimal. To see this, notice the entrepreneur will not invest for $\mu < \mu^m$ because:

$$\hat{x} + \mu^m - K - I - k^m = -k^m \leq 0.$$

In contrast, the entrepreneur will invest for all $\mu > \mu^m$ because the price of an uncertified asset will be:

$$P = \hat{x} + \frac{1}{2}[\mu^m + f] = \hat{x} + \frac{1}{2}[I - \hat{x} + K + f] = I + K + \frac{1}{2}[\hat{x} - I - K + f] > I + K. \qquad \text{(A11)}$$

The inequality in (A11) follows from Assumption 3. This investment pattern provides the following expected welfare, as claimed:

$$
\begin{aligned}
W^{NV} &= \int_{\mu^m}^{f} [\hat{x} - I - K + \tilde{\mu}]\frac{d\tilde{\mu}}{2f} \\
&= \frac{1}{2f}[\hat{x} - I - K][f - \mu^m] + \frac{1}{4f}[f^2 - (\mu^m)^2] \\
&= \frac{1}{4f}[f - \mu^m][2\hat{x} - 2I - 2K + f + I - \hat{x} + K] \\
&= \frac{[f + \hat{x} - I - K]^2}{4f}. \qquad \text{(A12)}
\end{aligned}
$$

From (A12), the difference between expected welfare in the presence of a nontrivial MC policy and in its absence is:

$$G(K) \equiv \frac{[f-I+\hat{x}-K]^2}{4f} - [\hat{x}-I]$$

$$= \frac{1}{4f}\{[\hat{x}-I]^2 + [f-K]^2 + 2[f-K][\hat{x}-I] - 4f[\hat{x}-I]\}$$

$$= \frac{1}{4f}\{[f+I-\hat{x}+K]^2 - 4fK\}. \tag{A13}$$

Honoring the limits of integration in (A12) and (A13) implies $G(K) > 0$ for $K < [\sqrt{f} - \sqrt{\hat{x}-I}]^2$ while $G(K) \leq 0$ for $K \in [[\sqrt{f} - \sqrt{\hat{x}-I}]^2, f+\hat{x}-I]$. Likewise, for $K > f+\hat{x}-I$, no investment is induced under a nontrivial MC policy. ■

PROOF OF PROPOSITION 2

The conclusion in the proposition follows immediately from a comparison of expected welfare when VC arises and MC is not imposed (W^{NM}, as specified in (A2)) and expected welfare when nontrivial MC arises in the absence of VC (W^{NV}, as specified in (A12)). ■

PROOF OF PROPOSITION 3

The proof follows from the following five conclusions.

Conclusion 1

If the regulator implements a trivial MC policy by setting μ^m below $-f$, then expected welfare is as specified in Lemma 1 (A2):

$$W_1 = W^{NM}. \tag{A14}$$

Conclusion 2

If the regulator sets μ^m above f, then underinvestment is induced and expected welfare is:

$$W_2 = \frac{[f+\hat{x}-I-K-k^m]^2}{4f}. \tag{A15}$$

Proof: Define μ^* to be the smallest realization of $\tilde{\mu}$ for which the entrepreneur will invest. In this case, μ^* is determined by:

$$\hat{x}+\mu^*-K-k^m = I, \quad \text{or } \mu^* = I-\hat{x}+K+k^m. \tag{A16}$$

Assumption 3 ensures $\mu^* < f$. Therefore, expected welfare in this case is:

$$W_2 = \int_{\mu^*}^{f} [\hat{x}+\tilde{\mu}-I-K-k^m]\frac{d\tilde{\mu}}{2f}$$

$$= \frac{[f+\hat{x}-I-K-k^m]^2}{4f}.$$

Conclusion 3

$k^v \le \frac{f+\hat{x}-I-K}{3}$ implies expected welfare under a nontrivial MC policy (i.e., one in which $-f \le \mu^m \le f$) is:

$$W_3 = \frac{[f+\hat{x}-I-K-k^m]^2}{4f} + \frac{k^m k^v}{f}. \tag{A17}$$

Proof: First suppose $\mu^m \le I-\hat{x}+K-k^v$. In this case, equilibrium behavior results in all investments being offered for sale on the basis of voluntary certification. No investment is undertaken for $\mu < \mu^m$ because:

$$\hat{x}+\mu-I-K-k^m < -k^v-k^m < 0.$$

In contrast, if $\mu \ge I-\hat{x}+K+k^v \equiv \mu^v$, investment followed by voluntary certification provides non-negative profit:

$$\hat{x}+\mu-I-K-k^v \ge \hat{x}+(I-\hat{x}+K+k^v)-I-K-k^v = 0.$$

No market for uncertified investments will develop in this case because the price of an uncertified asset in such a market would be less than $I+K$. This is the case because the assumed off-equilibrium beliefs imply:

$$\begin{aligned} P &= \hat{x}+\frac{1}{2}[\mu^m - f] \le \hat{x}+\frac{1}{2}[\mu^m+\mu^v] \\ &= \hat{x}+\frac{1}{2}[\mu^m+I-\hat{x}+K+k^v] \\ &= \frac{1}{2}[\mu^m+I+\hat{x}+K+k^v]. \end{aligned} \tag{A18}$$

When $\mu^m \le I-\hat{x}+K-k^v$, (A18) implies:

$$P \le \frac{1}{2}[I-\hat{x}+K-k^v+I+\hat{x}+K+k^v] = I+K.$$

When $k^v \le \frac{f+\hat{x}-I-K}{3}$, $\mu^v < f$. Therefore, expected welfare in this case is:

$$\begin{aligned} W_{31} &= \frac{1}{2f}\int_{\mu^v}^{f}[\hat{x}+\tilde{\mu}-I-K-k^v]d\tilde{\mu} \\ &= \frac{1}{2f}[\hat{x}-I-K-k^v][f-\mu^v] + \frac{1}{4f}[f^2-(\mu^v)^2] \\ &= \frac{1}{2f}[\hat{x}-I-K-k^v][f-I+\hat{x}-K-k^v] + \frac{1}{4f}[f^2-(I-\hat{x}+K+k^v)^2] \\ &= \frac{[\hat{x}-I-K-k^v]^2+2f[\hat{x}-I-K-k^v]+f^2}{4f} \\ &= \frac{[f+\hat{x}-I-K-k^v]^2}{4f}. \end{aligned} \tag{A19}$$

Second, suppose $I-\hat{x}+K-k^v \le \mu^m \le I-\hat{x}+K+k^m$. In this case, the entrepreneur will not invest when $\mu < \mu^m$ because he can secure greater (zero) profit by not investing:

$$\hat{x}+\mu-I-K-k^m<\hat{x}+\mu^m-I-K-k^m\leq\hat{x}+(I-\hat{x}+K+k^m)-I-K-k^m=0.$$

If $\mu\geq\mu^m$, then the entrepreneur will undertake the investment project and sell his uncertified asset at price:

$$P=\hat{x}+\frac{1}{2}[\mu^m+\mu^v], \tag{A20}$$

where μ^v is the smallest realization of $\tilde{\mu}$ for which entrepreneur will invest and voluntarily certify at incremental cost of k^v:

$$\hat{x}+\mu^v-k^v=P,\quad \text{or } \mu^v=P-\hat{x}+k^v. \tag{A21}$$

(A20) and (A21) imply:

$$P=\hat{x}+k^v+\mu^m, \tag{A22}$$

$$\mu^v=\mu^m+2k^v. \tag{A23}$$

Expected welfare in this case is:

$$\begin{aligned}W_{32}&=\int_{\mu^m}^{\mu^v}[P-I-K]\frac{d\tilde{\mu}}{2f}+\int_{\mu^v}^{f}[\hat{x}+\tilde{\mu}-I-K-k^v]\frac{d\tilde{\mu}}{2f}\\&=\frac{1}{2f}[P-I-K][\mu^v-\mu^m]+\frac{1}{2f}[\hat{x}-I-K-k^v][f-\mu^v]+\frac{1}{4f}[f^2-(\mu^v)^2]\\&=\frac{k^{v2}}{f}+\frac{f^2+2f[\hat{x}-I-K-k^v]}{4f}-\frac{(\mu^m)^2}{4f}-\frac{[\hat{x}-I-K-k^v]\mu^m}{2f}.\end{aligned} \tag{A24}$$

From (A24):

$$\frac{dW_{32}}{d\mu^m}=\frac{I-\hat{x}+K+k^v-\mu^m}{2f}\geq 0. \tag{A25}$$

The inequality in (A25) holds because $\mu^m\leq I-\hat{x}+K+k^m\leq I-\hat{x}+K+k^v$, where the last inequality holds because $k^v\geq k^m$, by assumption. Therefore, the optimal MC policy is $\mu^m=I-\hat{x}+K+k^m$.

From (A22):

$$P=\hat{x}+k^v+I-\hat{x}+K+k^m=k^v+I+K+k^m>I+K.$$

Also, from (A23):

$$\mu^v=I-\hat{x}+K+k^m+2k^v<f. \tag{A26}$$

The inequality in (A26) holds because $k^v\geq k^m$ and $k^v\leq\frac{f+\hat{x}-I-K}{3}$, by assumption. Substituting $\mu^m=I-\hat{x}+K+k^m$ into (A24) provides:

$$W_{32} = \frac{k^{v^2}}{f} + \frac{f^2 + 2f[\hat{x} - I - K - k^v]}{4f} - \frac{[I - \hat{x} + K + k^m]^2}{4f} - \frac{[\hat{x} - I - K - k^v][I - \hat{x} + K + k^m]}{2f}$$

$$= \frac{k^{v^2}}{f} + \frac{1}{4f}\{f^2 + 2f[\hat{x} - I - K - k^v] - [I - \hat{x} + K + k^m]^2 - 2[\hat{x} - I - K - k^v][I - \hat{x} + K + k^m]\}$$

$$= \frac{k^{v^2}}{f} + \frac{1}{4f}\{f^2 + 2f[\hat{x} - I - K - k^v] - [I - \hat{x} + K + k^m][k^m + \hat{x} - I - K - 2k^v]\}. \tag{A27}$$

Third, suppose $I - \hat{x} + K + k^m < \mu^m \leq f - 2k^v$. In this case, the entrepreneur will invest whenever $\mu \geq \mu^* = I - \hat{x} + K + k^m$ and certify the value of his asset at incremental cost k^m because:

$$\hat{x} + \mu - K - k^m \geq \hat{x} + I - \hat{x} + K + k^m - K - k^m = I.$$

If $\mu \in [\mu^m, \mu^v)$, the entrepreneur will also invest, but will sell an uncertified asset at the price specified in (A22). For $\mu \geq \mu^v = \mu^m + 2k^v$, the entrepreneur will invest and voluntarily certify. Therefore, expected welfare is:

$$W_{33} = \int_{\mu^*}^{\mu^m} [\hat{x} + \tilde{\mu} - I - K - k^m]\frac{d\tilde{\mu}}{2f} + \int_{\mu^m}^{\mu^v} [P - I - K]\frac{d\tilde{\mu}}{2f} + \int_{\mu^v}^{f} [\hat{x} + \tilde{\mu} - I - K - k^v]\frac{d\tilde{\mu}}{2f}$$

$$= \frac{1}{2f}[\hat{x} - I - K - k^m][\mu^m - \mu^*] + \frac{1}{4f}[(\mu^m)^2 - (\mu^*)^2] + \frac{1}{2f}[P - I - K][\mu^v - \mu^m]$$

$$+ \frac{1}{2f}[\hat{x} - I - K - k^v][f - \mu^v] + \frac{1}{4f}[f^2 - (\mu^v)^2]$$

$$= \frac{1}{2f}[k^v - k^m][\mu^m] + \frac{[\hat{x} - I - K - k^m]^2 + f^2 + 4k^{v^2} + 2f[\hat{x} - I - K - k^v]}{4f}. \tag{A28}$$

(A28) implies W_{33} is increasing in μ^m. Therefore, the optimal MC policy in this case is $\mu^m = f - 2k^v$.

Notice that $\mu^* < \mu^m$ when $k^v \leq \frac{f + \hat{x} - I - K}{3}$ and $k^v \geq k^m$. Also, (A22) implies:

$$P = \hat{x} + k^v + f - 2k^v = f + \hat{x} - k^v > I + K. \tag{A29}$$

The inequality in (A29) holds because $k^v \leq \frac{f + \hat{x} - I - K}{3}$, by assumption. No voluntary certification arises in this setting because (A23) implies:

$$\mu^v = f - 2k^v + 2k^v = f.$$

Substituting $\mu^m = f - 2k^v$ into (A28) provides:

$$W_{33} = \frac{1}{2f}[k^v - k^m][f - 2k^v] + \frac{[\hat{x} - I - K - k^m]^2 + f^2 + 4k^{v^2} + 2f[\hat{x} - I - K - k^v]}{4f}$$

$$= \frac{[\hat{x} - I - K - k^m]^2 + f^2 + 2f[\hat{x} - I - K - k^v] + 2f[k^v - k^m]}{4f} + \frac{k^m k^v}{f}$$

$$= \frac{[f + \hat{x} - I - K - k^m]^2}{4f} + \frac{k^m k^v}{f}. \tag{A30}$$

Fourth, suppose $f - 2k^v \leq \mu^m \leq f$. In this case, the entrepreneur will invest and certify at incremental cost k^m when $\mu \geq \mu^* = I - \hat{x} + K + k^m$.

If $\mu \geq \mu^m$, then the entrepreneur will invest and sell his uncertified asset at price:

$$P = \hat{x} + \frac{1}{2}[\mu^m + f] \geq f + \hat{x} - k^v > I + K. \tag{A31}$$

The second inequality in (A31) holds because $k^v \leq \frac{f+\hat{x}-I-K}{3}$, by assumption.

No VC arises when $\mu \in (\mu^m, f]$ because voluntary certification reduces profit:

$$\hat{x} + \mu - I - K - k^v \leq \hat{x} + f - I - K - k^v \leq P - I - K. \tag{A32}$$

The second inequality in (A32) follows from (A31) when $\mu^m \geq f - 2k^v$.

Expected welfare in this case is:

$$\begin{aligned} W_{34} &= \int_{\mu^*}^{\mu^m} [\hat{x} + \tilde{\mu} - I - K - k^m]\frac{d\tilde{\mu}}{2f} + \int_{\mu^m}^{f} [P - I - K]\frac{d\tilde{\mu}}{2f} \\ &= \frac{1}{2f}[\hat{x} - I - K - k^m][\mu^m - \mu^*] + \frac{1}{4f}[(\mu^m)^2 - (\mu^*)^2] + \frac{1}{2f}[P - I - K][f - \mu^m] \\ &= \frac{[\hat{x} - I - K - k^m]^2 + f^2 + 2f[\hat{x} - I - K]}{4f} - \frac{k^m \mu^m}{2f}. \end{aligned} \tag{A33}$$

(A33) implies W_{34} is decreasing in μ^m. Therefore, the optimal MC policy is $\mu^m = f - 2k^v$, just as in the prior case. Therefore, $W_{34} = W_{33}$. Expected welfare in this setting is:

$$W_{34} = \frac{[f + \hat{x} - I - K - k^m]^2}{4f} + \frac{k^m k^v}{f}.$$

When a nontrivial MC policy is imposed, the optimal MC policy generates expected welfare:

$$W_3 = \max\{W_{31}, W_{32}, W_{33}, W_{34}\}.$$

From (A30) and (A19):

$$W_{33} - W_{31} = \frac{[f + \hat{x} - I - K - k^m]^2}{4f} + \frac{k^m k^v}{f} - \frac{[f + \hat{x} - I - K - k^v]^2}{4f} > 0. \tag{A34}$$

The inequality in (A34) holds because $k^v \geq k^m$, by assumption. From (A30) and (A27):

$$\begin{aligned} W_{33} - W_{32} &= \frac{[f + \hat{x} - I - K - k^m]^2}{4f} + \frac{k^m k^v}{f} - \frac{k^{v^2}}{f} \\ &\quad - \frac{f^2 + 2f[\hat{x} - I - K - k^v] - [I - \hat{x} + K + k^m][k^m + \hat{x} - I - K - 2k^v]}{4f} \\ &= \frac{[f + \hat{x} - I - K - k^m][k^v - k^m]}{2f} + \frac{[k^m - k^v]k^v}{f} \\ &= \frac{[f + \hat{x} - I - K - k^m - 2k^v][k^v - k^m]}{2f} > 0. \end{aligned} \tag{A35}$$

The inequality in (A35) holds because $k^v \geq k^m$ and $k^v \leq \frac{f+\hat{x}-I-K}{3}$, by assumption. Therefore, $W_3 = W_{33}$.

P 31444

Conclusion 4

The optimal MC policy entails $\mu^m > f$ if and only if $k^m = 0$.

Proof: From (A15) and (A17):

$$W_2 - W_3 = \frac{[f + \hat{x} - I - K - k^m]^2}{4f} - \frac{[f + \hat{x} - I - K - k^m]^2}{4f} - \frac{k^m k^v}{f}$$

$$= -\frac{k^m k^v}{f} \le 0. \tag{A36}$$

The inequality in (A36) holds strictly unless $k^m = 0 (\le k^v)$.

Conclusion 5

Suppose $K + k^m < \min\{\bar{k}^v, [\sqrt{f} - \sqrt{\hat{x} - I}]^2\}$. Then the optimal MC policy is a nontrivial policy that generates expected welfare W_3, as specified in (A17).

Proof: From (A36), $W_2 < W_3$ unless $k^m = 0$. We now compare W_1 and W_3 when $k^m > 0$. First suppose $\bar{k}^v > f$. Then (A17) and (A8) imply:

$$\frac{[f + \hat{x} - I - K - k^m]^2}{4f} + \frac{k^v k^m}{f} - [\hat{x} - I] = \frac{1}{4f}\{[f + \hat{x} - I - K - k^m]^2 + 4k^v k^m - 4f[\hat{x} - I]\}$$

$$> 0. \tag{A37}$$

The inequality in (A37) holds because:

$$4f[\hat{x} - I] \le [f + \hat{x} - I - K - k^m]^2, \tag{A38}$$

as $K + k^m < [\sqrt{f} - \sqrt{\hat{x} - I}]^2$, by assumption.

Now suppose $\bar{k}^v \in [f - \hat{x} + I, f]$. From (A17) and (A7), the increase in expected welfare secured by a nontrivial MC policy is:

$$J(\bar{k}^v) \equiv \frac{[f + \hat{x} - I - K - k^m]^2}{4f} + \frac{k^v k^m}{f} - \left[\hat{x} - I - \bar{k}^v + \frac{(\bar{k}^v)^2}{f}\right]. \tag{A39}$$

(A39) implies $J'(\bar{k}^v) < 0$. Moreover, $J(f) \ge 0$ when $K + k^m < [\sqrt{f} - \sqrt{\hat{x} - I}]^2$ from (A37) and (A38). Therefore, $J(\bar{k}^v) \ge 0$ and so $W_3 \ge W_1$ for all $\bar{k}^v \in [f - \hat{x} + I, f]$.

Now suppose $\bar{k}^v < f - \hat{x} + I$. From (A17) and (A2), the increase in expected welfare secured by a nontrivial MC policy is:

$$M(\bar{k}^v) = \frac{[f + \hat{x} - I - K - k^m]^2}{4f} + \frac{k^v k^m}{f} - \frac{[f + \hat{x} - I - \bar{k}^v]^2}{4f}$$

$$= \frac{1}{4f}\{[f + \hat{x} - I - K - k^m]^2 + 4k^v k^m - [f + \hat{x} - I - \bar{k}^v]^2\}. \tag{A40}$$

(A40) implies $M(\bar{k}^v) > 0$ when:

$$K + k^m < f + \hat{x} - I - \sqrt{[f + \hat{x} - I - \bar{k}^v]^2 - 4k^v k^m}. \tag{A41}$$

The expression to the right of the inequality in (A41) is positive because it is increasing in $\bar{k}^v$ and because it is non-negative at $\bar{k}^v = 0$:

$$f+\hat{x}-I-\sqrt{[f+\hat{x}-I]^2-4k^v k^m} \geq f+\hat{x}-I-\sqrt{[f+\hat{x}-I]^2}=0.$$

The inequality in (A41) holds whenever $K+k^m<\bar{k}^v$, as this implies:

$$K+k^m<f+\hat{x}-I-\sqrt{[f+\hat{x}-I-\bar{k}^v]^2-4k^v k^m}.$$

∎

PROOF OF PROPOSITION 4

The welfare ranking in the proposition follows directly from Propositions 2 and 3 when $k^m>0$. When $k^m=0$, the proof of Proposition 3 reveals that when $k^v \leq \frac{f+\hat{x}-I-K}{3}$ and $K+k^m < \min\{\bar{k}^v, [\sqrt{f}-\sqrt{\hat{x}-I}]^2\}$ we have:

$$W_2=W_3=\frac{[f+\hat{x}-I-K]^2}{4f}>W^{NM}.$$

∎

REFERENCES

Akerlof, G. 1970. The market for "lemons:" Quality uncertainty and the market mechanism. *The Quarterly Journal of Economics* 84 (August): 488–500.

Alciatore, M., C. Dee, P. Easton, and N. Spear. 1998. Asset write-downs: A decade of research. *Journal of Accounting Literature* 17 (Spring): 1–39.

Andreoni, J., B. Erard, and J. Feinstein. 1998. Tax compliance. *Journal of Economic Literature* 36 (June): 818–860.

Arya, A., H. Frimor, and B. Mittendorf. 2007. Discretionary vs. mandatory disclosures in a multi-segment firm. Working paper, The Ohio State University, Columbus, OH.

Bachar, J., N. Melumad, and G. Weyns. 1997. On cost tradeoffs between conservative and market value accounting. *Review of Accounting Studies* 2 (March): 7–34.

Dye, R. 2001. An evaluation of "Essays on disclosure" and the disclosure literature in accounting. *Journal of Accounting and Economics* 32 (December): 181–235.

Hope, O. 2003. Disclosure practices, enforcement of accounting standards, and analysts' forecast accuracy: An international study. *Journal of Accounting Research* 41 (May): 235–272.

Kanodia, C., and D. Lee. 1998. Investment and disclosure: The disciplinary role of periodic performance reports. *Journal of Accounting Research* 36 (Spring): 33–55.

Reis, R., and P. Stocken. 2007. Strategic consequences of historical cost and fair value measurements. *Contemporary Accounting Research* 24 (Summer): 557–584.

Riedl, E. 2004. An examination of long-lived asset impairments. *The Accounting Review* 79 (July): 823–852.

Stocken, P. 2000. Credibility of voluntary disclosure. *The Rand Journal of Economics* 31 (Summer): 359–374.

Verrecchia, R. 1983. Discretionary disclosure. *Journal of Accounting and Economics* 5 (December): 179–194.

———. 2001. Essays on disclosure. *Journal of Accounting and Economics* 32 (December): 97–180.

THE ACCOUNTING REVIEW
Vol. 83, No. 4
2008
pp. 893–913

American Accounting Association
DOI: 10.2308/accr.2008.83.4.893

The Effects of Disseminating Relative Performance Feedback in Tournament and Individual Performance Compensation Plans

R. Lynn Hannan
Georgia State University

Ranjani Krishnan
Michigan State University

Andrew H. Newman
Georgia State University

ABSTRACT: This study investigates the effects of relative performance feedback and incentive compensation method on performance. We examine whether the presence and the content of relative performance feedback have different effects on performance when participants are compensated via a tournament or an individual incentive scheme. Our experimental results show a disordinal interaction between incentive scheme and feedback. Specifically, providing relative performance feedback *improves* the mean performance of participants compensated under an individual incentive scheme regardless of the precision or specific content of the feedback. In contrast, providing relative performance feedback *deteriorates* the mean performance of participants compensated under a tournament incentive scheme, but only if the feedback is sufficiently precise. Supplementary analysis suggests that this deterioration in performance is due to ineffective task strategies rather than reduced effort. We also find that in the absence of relative performance feedback, participants compensated under a tournament incentive scheme perform better, and their performance improves to a greater extent over time, compared to participants compensated under an individual incentive scheme. These results have implications for the design of accounting, control, and reporting systems in firms.

Keywords: *compensation; feedback; tournaments; incentives.*

Data Availability: *Data are available from the authors on request.*

We thank Tony Chen, Bryan Church, Marlys Lipe, Joan Luft, Tim Mitchell, Sean Peffer, Mike Shields, Geoff Sprinkle, Michael Williamson, Bill Waller, two anonymous reviewers, workshop participants at Georgia Institute of Technology, Georgia State University, Michigan State University, University of Kentucky, University of Washington, York University, and participants at the 2007 American Accounting Association Management Accounting Conference, the 2007 Global Management Accounting Research Conference, and the 2007 American Accounting Association Annual Meeting for their thoughtful comments. We also thank Geoff Sprinkle for sharing his experimental instrument and Seth Pratt for writing the computer program.

Editor's note: This paper was accepted by Marlys Gascho Lipe.

Submitted: February 2007
Accepted: November 2007
Published Online: July 2008

I. INTRODUCTION

This study examines the effect of relative performance feedback on participants' performance when they are evaluated and compensated based on a tournament incentive scheme or an individual incentive scheme. Specifically, we investigate whether the presence and the content of relative performance feedback has different effects on performance when participants are compensated via a tournament incentive scheme compared to an individual incentive scheme. In addition, we investigate whether a tournament incentive scheme results in higher performance compared to an individual incentive scheme.

Tournament schemes of evaluating and rewarding performance are pervasive in the corporate world (McGregor 2006; Lambert et al. 1993; O'Reilly et al. 1988). A tournament incentive scheme can be defined as a compensation scheme where employees or managers are ranked on an ordinal scale based on their output and compensated according to their rank. The winner of the tournament receives the highest prize (such as bonus or promotion) and the size of the prize is not required to be a function of either the performance differential or actual performance. Economists have examined the circumstances under which tournaments produce superior outcomes to other forms of compensation such as fixed pay, or piece-rate (i.e., individual incentive) schemes; however, prior literature has not examined how relative performance feedback can influence performance in tournament incentive schemes.[1]

Although accountants have extensively studied performance measurement and incentive compensation, the focus of extant literature has been on examining how the properties of performance measures influence incentive contracting (for reviews see, Bushman and Smith 2001; Gibbons 1998; Murphy 1999; Prendergast 1999). These properties include, for example, how informative a measure is about agents' actions (Holmstrom 1979), the sensitivity of the measure to the manager's actions, the precision with which it is measured (Banker and Datar 1989), and its relation to other performance measures (Feltham and Xie 1994). Accounting literature on how the characteristics of the information system influence choices and performance under various incentive schemes is sparse (Sprinkle 2003). Research on how incentive schemes and feedback, individually or in conjunction, may affect performance is important because accountants play a major role in designing compensation plans (Atkinson et al. 2001; Indjejikian 1999) as well as in providing information and feedback to decision makers (Bonner and Sprinkle 2002). In order to design effective compensation and information systems, it is important to understand which incentive schemes are more efficient at motivating performance and the role of feedback in improving performance. This understanding can help in structuring incentive schemes and information systems that best align employees' interests with that of the firm. Our study contributes to this body of knowledge.

We investigate how relative performance feedback and incentive schemes affect performance using an experiment. We manipulate relative performance feedback (none, coarse, fine) and incentive compensation scheme (tournament or individual). Feedback is provided at specified times throughout the experiment and can be thought of as three types of accounting systems: one where no benchmarking data are disseminated to competing managers during the evaluation cycle, the second where coarse or noisy data are disseminated throughout the evaluation cycle, and the third where more precise data are disseminated throughout the evaluation cycle. Although hybrid compensation schemes exist in practice, for experimental control purposes, we use only pure tournament or individual schemes.

---

[1] The focus of our study is on a specific form of relative performance contract, i.e., a tournament incentive scheme, where the incentive compensation is solely a function of rank. Archival studies have explored a related area, i.e., whether relative performance affects managers' compensation awards. For example, a firm's ROA standard (or other performance measure) may be evaluated relative to the industry average (e.g., Antle and Smith 1986; Gibbons and Murphy 1990; Jensen and Murphy 1990). However, these studies focus on the *prevalence* of relative standards and not the *impact* of such standards on managerial actions.

Our experimental results show a disordinal interaction between feedback and incentive scheme.[2] Specifically, providing relative performance feedback *improves* the mean performance of participants compensated under an individual incentive scheme, regardless of the precision or the specific content of the feedback. That is, the performance of participants in the individual incentive condition improved regardless of what the feedback revealed about their relative performance. In contrast, providing relative performance feedback *deteriorates* the mean performance of participants compensated under a tournament incentive scheme, but only if the feedback is sufficiently precise. Supplementary analysis reveals that the deterioration in mean performance caused by providing relative performance feedback in the tournament condition results from a decline in performance by most participants whose performance in the first half of the tournament was below the 80th percentile. The analysis indicates that the decline in performance is not because these participants reduced their effort but rather because they adopted ineffective task strategies. In addition, we find that in the *absence* of relative performance feedback, participants compensated under a tournament incentive scheme perform better, and their performance improves to a greater extent over time, compared to participants compensated under an individual incentive scheme. This finding is consistent with economic theory related to tournaments. However, the performance advantage of tournament schemes disappears once relative performance feedback is introduced.

Our study has several implications for the design of compensation and information systems. Our results imply that the effect of relative performance feedback depends on the type of incentive scheme. Whereas providing relative performance feedback is likely to have positive consequences when managers are compensated via an individual incentive scheme, such feedback may have negative consequences when managers are compensated via a tournament incentive scheme. This finding is interesting because it is generally believed that feedback improves performance and that more refined accounting systems are helpful in decision making (Cooper et al. 1992; Cooper and Kaplan 1998). Our results show that, as suggested by Kluger and DeNisi (1996), feedback may not always be a positive force. If providing information on peers reduces the mean performance of managers and consequently reduces firm performance, as our study indicates, disseminating such information may have negative consequences.

The remainder of this paper is organized as follows. The following section summarizes the theory of tournaments and individual incentive schemes and develops hypotheses. Section III describes the experiment. Section IV reports the results. Conclusions and implications are discussed in Section V.

II. THEORY AND HYPOTHESES

Effects of Relative Performance Feedback

In this section, we draw on economic and psychological theories to develop hypotheses related to the effects of relative performance feedback *within* the tournament and individual incentive schemes. Because performance feedback systems can differ in terms of the quality of relative performance information that is provided, we explore two levels of feedback by varying the precision of the feedback's content. We vary the precision of the content by varying the number of partitions into which we divide the relative performance feedback (halves and deciles), and call these two levels of feedback "coarse" and "fine." Accordingly, a participant provided with coarse feedback can assess whether he is above or below the mean, but not the specific percentile of his relative performance. Fine feedback provides a more precise assessment of the participant's rank, to the actual performance decile.

---

[2] Our results and implications relate to the pure tournament or pure individual schemes investigated in our study.

Individual Incentive Scheme

From an economic theory perspective, relative performance feedback should not affect performance in an individual incentive scheme because compensation is based solely on individual performance. However, psychology theories predict that providing relative performance feedback will affect performance even in the absence of pecuniary considerations. Social comparison theory (Festinger 1954) posits that individuals have a drive to continually compare themselves to others in order to evaluate their own abilities. Individuals want to do well relative to others, and when they perform worse than others, their sense of self-identity suffers (Tesser and Campbell 1980). Thus, managers are likely to be motivated to avoid this loss of self-identity when subjected to relative performance feedback. As a result of this boost in motivation, performance will improve.[3] Relative performance feedback can also help individuals to assess whether they are using erroneous hypotheses, and prior research suggests that such feedback can augment performance by facilitating learning and appropriate effort allocation (Kessler and Ashton 1981; Kluger and DeNisi 1996). Hence, we predict that the increased motivation and learning created by relative performance feedback will result in improved performance over time compared to when no feedback is provided. We predict that the increase in performance will occur in both the coarse and the fine feedback conditions.

H1a: When participants are compensated based on an individual incentive scheme, performance will improve to a greater extent when they are provided with *coarse* relative performance feedback compared to *no feedback* about relative performance.

H1b: When participants are compensated based on an individual incentive scheme, performance will improve to a greater extent when they are provided with *fine* relative performance feedback compared to *no feedback* about relative performance.

We do not expect that the increase in performance will be different across the two feedback conditions because our hypotheses predict a motivating effect from the *presence* of feedback, rather than the *content* of feedback.

Tournament Incentive Schemes

Both economic and psychology theories predict that the effect of relative performance feedback under tournament incentive schemes depends on how such feedback affects perceptions of the manager's relative standing in the tournament. Specifically, from an economic theory perspective, as the probability of winning the tournament increases, the marginal effect of effort increases, thereby motivating increased effort (ignoring any nonlinearities in disutility for effort). To the extent relative performance feedback can facilitate managers' probabilistic assessments, relative performance feedback should increase effort for higher performing participants. Psychology theories predict that feedback can increase effort if the feedback indicates that the goal (i.e., the bonus) is attainable, because such feedback has cognitive effects such as increasing goal commitment (Locke and Latham 1990) and perceptions of self-efficacy (Bandura 1991), as well as positive effects on motivation (Kluger and DeNisi 1996).

---

[3] Frederickson (1992) provided feedback at the *end of the evaluation cycle* and investigated whether changing the degree of common uncertainty affected effort. From a psychological perspective, increased saliency of comparison of others motivates higher effort, and therefore, to the extent that increases in common uncertainty increases saliency, effort increases. Frederickson found that increases in common uncertainty increased effort in the tournament condition, but not in the individual condition. Our experiment provides relative performance feedback *throughout the evaluation cycle*. Our design is likely to have a stronger saliency effect because feedback is more frequent and its form is more direct compared to changes in common uncertainty.

Similarly, economic theory predicts that as the probability of winning the bonus decreases, the marginal effect of effort decreases, which in turn reduces effort. Likewise, from a psychology theory perspective, when goals are perceived to be unattainable, individuals give up (Locke and Latham 1990), resulting in lower performance. Consistent with this notion, prior research has shown that participants in a tournament incentive scheme, who think that they will not be able to catch up, tend to reduce their effort (Casas-Arce and Martinez-Jerez 2007; Muller and Schotter 2003; Young et al. 1993). In addition, the performance of those who are falling behind but have not given up may still deteriorate because they exert cognitive effort on non-task-related activities such as designing a competitive strategy or worrying about their performance, thereby reducing the effort available for task-related strategy (Kanfer and Ackerman 1989) or they try risky strategies since they believe they have nothing to lose (Camerer and Hogarth 1999).

In our experimental setting, participants whose performance is in the top 10 percent compared to other participants receive a bonus. Coarse feedback, which provides an assessment of whether a participant's performance is above or below the mean, is likely to have offsetting effects on performance. Although some participants (whose performance is below the mean) will interpret the feedback as indicating that the bonus is unattainable and decrease effort, others (whose performance is above the mean) will interpret the feedback as indicating that the bonus is attainable and increase effort. Thus, the performance of some participants will increase, while that of others will decrease, resulting in no overall effect on mean performance. As a result, we predict that the performance improvement will be the same when coarse feedback is provided as when no feedback about relative performance is provided. We acknowledge that our prediction is for a null hypothesis, which accordingly should be interpreted with caution.

H2a: When participants are compensated based on a tournament incentive scheme, change in performance will not differ when they are provided with *coarse* relative performance feedback compared to *no feedback* about relative performance.

We predict that fine feedback will have a different effect on performance. Participants, who are not in the top one or two deciles of performance, will likely perceive the relative feedback as indicating that they have a very low or zero probability of attaining the bonus. Thus, a majority of participants will become demotivated and decrease effort. Alternatively, these participants may devote more effort to competitive rather than task strategies, or try risky strategies that are unlikely to work out. As a result, performance will worsen when participants are provided with fine feedback compared to no feedback or coarse feedback. Therefore, we present the following hypotheses:

H2b: When participants are compensated based on a tournament incentive scheme, performance will increase to a lesser extent when they are provided with *fine* relative performance feedback compared to *no feedback* about relative performance.

H2c: When participants are compensated based on a tournament incentive scheme, performance will increase to a lesser extent when they are provided with *fine* relative performance feedback compared to *coarse* relative performance feedback.

Comparison between Tournament versus Individual Incentive Schemes

Our third set of hypotheses compares performance under a tournament to an individual incentive scheme. We base our predictions on analytical models.[4] Because these models do not address the effects of providing relative performance information before the end of the evaluation period, we restrict our predictions to when participants receive no feedback about their relative performance feedback during the evaluation period. This type of information setting is analogous to an organization where an individual's performance and bonus information is kept confidential from other individuals or to recruitment and promotion processes where participants may have knowledge of who is competing, but not the relative ranks.

The first formal theoretical model of tournaments is generally attributed to Lazear and Rosen (1981) who model rank-order tournaments, where an agent's payment depends only on the rank of his or her performance.[5] Their model consists of a risk-neutral principal and two agents. Each manager's performance is a linear function of his effort μ_i and a random error term that can be decomposed into two components, ε_i and θ. While ε_i represents an individualistic or idiosyncratic error term that is specific to a particular manager, θ is a common or systematic error that is shared by all the managers (Nalebuff and Stiglitz 1983).[6] The contract is signed before ε and θ are known. Subsequently, the manager observes θ and determines how much effort to expend.

If the manager is risk-averse, then the random error increases the manager's risk and, therefore, the firm would need to compensate the manager for bearing this risk. When the manager is compensated on an individual piece rate system, the total error is $\varepsilon_i + \theta$. However, when the manager is compensated based on a tournament, the common error term θ is eliminated because it influences both contestants. Lazear and Rosen (1981) show that if this common error is large and/or the manager is sufficiently risk averse, the tournament model produces superior outcomes compared to the individual piece rate model.

Prior literature has not directly tested the prediction of the analytical models that tournaments elicit higher effort compared to individual schemes in the presence of a common environmental error (see Bonner et al. [2000] for a review and meta-analysis of the effect of different types of incentive schemes on performance). For example, although Bull et al. (1987) find that participants in their experiments select effort levels that are consistent with economic predictions about tournaments as well as individual incentive contracts, they do not examine whether there are significant differences in the relative effectiveness of the two types of incentive schemes. Frederickson (1992) finds that participants receiving a bonus based on their performance relative to a group average select higher effort levels compared to those compensated based on individual performance only. However, because Frederickson (1992) induced risk neutrality in his experimental participants, the economic intuition behind this result is unclear. An archival study by Matsumura and Shin (2006) finds that performance increased following the implementation of a relative performance incentive plan for Korean postal stores and that performance was positively associated with the degree of common uncertainty.

---

[4] Consistent with these models, we investigate a setting where the winner takes the entire bonus. Although other types of tournament schemes exist in practice, such as those where the size of the bonus is contingent on performance rank, where piece rates and tournaments are used jointly, or where the loser is penalized, we use the simpler version analyzed in these models for our study.

[5] If the differences in performance are due to differences in ability, and the firm can sort managers based on ability, then handicapping systems can be used. In handicapping systems, the prizes and probability of reward are tailored to each participant. For example, marathon organizers provide incentives to champion runners to induce people to participate (O'Keefe et al. 1984). When participants are of similar ability however, handicap systems are not required.

[6] For example, ε_i could represent the individual manager's comparative advantage at the task, and θ the general level of difficulty of a task (Nalebuff and Stiglitz 1983). Alternatively, the accounting system could measure performance with noise, and this noise would be common to all managers (θ).

Based on the theoretical predictions of analytical models and the extant empirical findings, we predict that performance will be higher when participants are compensated based on a tournament compared to an individual incentive scheme. We also predict that this performance differential will increase over time because the higher effort expended by participants compensated via a tournament incentive scheme will facilitate learning.

H3a: In the absence of relative performance feedback, performance will be higher when compensation is based on a *tournament* incentive scheme compared to an *individual* incentive scheme.

H3b: In the absence of relative performance feedback, performance will improve more when compensation is based on *tournament* incentive scheme compared to an *individual* incentive scheme.

We do not make predictions for when participants are provided with coarse or fine relative performance feedback because performance across feedback conditions depends on the relative magnitude of the effects predicted in H1 and H2 to those predicted in H3.

Summary of Hypotheses

To summarize, we expect a disordinal interaction between relative performance feedback and incentive scheme. Specifically, relative performance feedback will have opposite effects for participants in the individual compared to the tournament incentive scheme. Under the individual incentive scheme, we expect change in performance to *be higher* for both the coarse and fine feedback conditions compared to the no feedback condition. In contrast, under the tournament scheme, we expect change in performance to *be lower* in the fine feedback condition compared to the coarse and none conditions. We also expect that in the absence of relative performance feedback, performance (change in performance) will be higher when individuals are compensated via a tournament compared to an individual incentive scheme.

III. METHOD

We use an experiment to test our hypotheses because this allows us to control the manipulation of the relative performance feedback system and the incentive scheme.

Participants

One hundred thirty-four business students at a large, public university participated in the experiment. Participants were recruited from upper-level undergraduate accounting classes. Of the participants, 26 percent were juniors, 66 percent were seniors, and 8 percent were post-baccalaureate students. Participation was voluntary. Participants received $5.00 plus any additional money earned during the experiment.

Experimental Procedures and Task Description

The procedures and task described in this section are the same for all conditions. Variations for feedback and incentive scheme manipulations are described in the next section.

Experimental sessions were conducted in a computer laboratory and lasted approximately one hour. Separate sessions were conducted for each incentive scheme and feedback condition. Instructions were read aloud to the participants by one of the authors. To ensure that participants understood the task and the computation of their pay, participants were required to take a computerized pre-experiment quiz. Each participant was required to score 100 percent on the quiz before beginning the actual experiment.[7]

The experimental task was adapted from Sprinkle (2000). Participants acted as managers and made output quantity decisions for a single product. The output decision in conjunction with a randomly determined state of nature determined the amount of profit points earned by the participant. Participants were not informed of the state of nature. Profit points for all potential combinations of output choices and states of nature are shown in Table 1. Participants received a similar table and they were provided with several examples to help them understand it. For example,

TABLE 1

Profit for Each Combination of Output Quantity and State of Nature[a]

	Output Quantity Choice																			
State of Nature	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**
1	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	5	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	5	5	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	5	5	10	20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	5	5	10	20	20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	5	5	10	20	20	30	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	5	5	10	20	20	30	30	0	0	0	0	0	0	0	0	0	0	0	0	0
8	5	5	10	20	20	30	30	30	0	0	0	0	0	0	0	0	0	0	0	0
9	5	5	10	20	20	30	30	30	45	0	0	0	0	0	0	0	0	0	0	0
10	5	5	10	20	20	30	30	30	45	45	0	0	0	0	0	0	0	0	0	0
11	5	5	10	20	20	30	30	30	45	45	60	0	0	0	0	0	0	0	0	0
12	5	5	10	20	20	30	30	30	45	45	60	60	0	0	0	0	0	0	0	0
13	5	5	10	20	20	30	30	30	45	45	60	60	60	0	0	0	0	0	0	0
14	5	5	10	20	20	30	30	30	45	45	60	60	60	80	0	0	0	0	0	0
15	5	5	10	20	20	30	30	30	45	45	60	60	60	80	80	0	0	0	0	0
16	5	5	10	20	20	30	30	30	45	45	60	60	60	80	80	95	0	0	0	0
17	5	5	10	20	20	30	30	30	45	45	60	60	60	80	80	95	95	0	0	0
18	5	5	10	20	20	30	30	30	45	45	60	60	60	80	80	95	95	95	0	0
19	5	5	10	20	20	30	30	30	45	45	60	60	60	80	80	95	95	95	100	0
20	5	5	10	20	20	30	30	30	45	45	60	60	60	80	80	95	95	95	100	100

[a] Participants selected an output quantity choice that, in conjunction with a randomly determined state of nature, determined the profit they earned. Participants received a similar table during the experiment.

---

[7] 83 percent of participants scored at least 90 percent, and all but one participant scored at least 70 percent on their initial quiz attempt. The high initial scores together with the requirement that the final score must be 100 percent indicates that participants understood the task and how they would be compensated.

suppose a participant chose an output of 11. If the random state of nature was a number from 1 to 10, then the participant would earn 0 profit points. If the random state of nature was a number from 11 to 20, the participant would earn 60 profit points.[8]

Participants made output decisions for 60 periods, which were divided into 12 trials of five periods each. The state of nature remained constant for each of the five periods within a trial. We used the same states of nature for the 12 trials as Sprinkle (2000). By using the same set of states of nature for each participant, the potential total profit point earnings were the same for all the participants. Thus, the common error, θ, was the same for all participants.

Because the state of nature remained constant within each trial, participants had the ability to update their beliefs about the expected profit of future alternative output choices by reviewing the profit points earned in each prior period of that trial. Participants were given the option to do so. Specifically, after making their output choice each period, participants were queried about whether they wanted to see their trial history, which would display their output choice and profit points for the current as well as all prior periods of the trial. However, viewing this trial history screen was costly. If a participant opted to view his trial history, then it would display for a minimum of ten seconds, thereby reducing the number of time points (described next) that a participant could earn.

To proxy for a disutility for effort, participants were awarded time points for completing a trial early. Specifically, for each trial they earned one time point for every second that they finished before the 180sec time limit had expired. They received cash payment of $0.25 for each 400 time points earned during the experiment. To help participants keep track of time, a clock that counted down from 180sec was displayed on all screens during the trial. The payment for time points was in addition to any earnings they received from earning profit points (individual condition) or the bonus (tournament condition).

At the end of each trial, a screen displayed a summary of the participant's output choices, profit points earned, and time points earned for the current trial. It also displayed a cumulative total of profit points and time points earned. Thus, each participant was provided with complete *individual* performance feedback.

At the end of the experiment, each participant completed a questionnaire, after which a screen displayed the participant's total earnings. The participant was paid in private and dismissed.

Experimental Design and Variables

The complete experimental design is a 3 × 2 × 12 × 3 mixed factorial design. The primary independent variables of interest are relative performance feedback, which has three levels (none, coarse, and fine) and incentive scheme, which has two levels (individual and tournament). These factors are manipulated between-subjects. The third factor, manipulated within-subjects, is trial, which has 12 levels. The fourth factor is order, manipulated between-subjects. We divided the 12 trials into four quarters, and then used three orders within each quarter. Because order has no effect ($F = 0.29$, $p = 0.75$), we exclude it from further discussion.

We use two primary dependent variables: (1) Performance, which is cumulative profit earned over the entire 60 periods (12 trials); and (2) Change in performance, which is fourth-quarter profit

---

[8] Eleven of the 20 options are dominated choices. For example, option 13 is dominated by options 11 and 12 because for all possible states of nature, options 11 and 12 produce a profit that is equal to that of option 13, and in addition, these options also produce a profit for states of nature where option 13 does not produce a profit (states 11 and 12 for option 11 and state 12 for option 12). Dominated choices are included to obtain a measure of task strategy effectiveness and are discussed as part of the supplemental analysis.

(trials 10, 11, 12) less first quarter profit (trials 1, 2, 3).[9] These dependent measures use one observation per participant, and so are independent observations for purposes of our statistical tests. By experimental design, the set of states of nature is the same in the first and fourth quarters (although the order is randomized within quarter). Therefore, the total profit potential is the same in the first and fourth quarters.

Relative Performance Feedback

The three levels of relative performance feedback were manipulated as follows: Participants in the *none* condition were not provided any information about their relative performance ranking during the decision-making portion of the experiment. Participants in the *coarse* condition were provided relative performance feedback at the end of each quarter, which specified whether their profit point performance was above or below the 50th percentile compared to previous participants. For example, if a participant's profit point performance placed him in the 82nd percentile, then he received a message stating, "The total profit points you have earned so far in the experiment places you above the 50th percentile." Participants in the *fine* condition were also provided relative performance feedback at the end of each quarter. However, their feedback was more precise compared to the coarse condition because it reported the deciles of the participant's profit point rank. For example, if an individual's profit point performance placed him in the 82nd percentile, then he received a message that stated, "The total profit points you have earned so far in the experiment places you in the 80-90th percentile."

At the end of the experiment, all participants received relative performance feedback in ten-percentile intervals, i.e., the same format as the fine condition. Thus, participants in the tournament condition could determine whether they earned the bonus regardless of their feedback condition.

Recall that within each quarter all participants had the same set of states of nature. Participants were informed that their feedback would be based on a comparison of previous participants who had received the same states, and who thus had identical profit point potential. In other words, participants were told that the common error, θ, was the same for all participants to whom they were being compared.[10]

Incentive Scheme

The two levels of incentive scheme were manipulated as follows: Participants in the *individual* incentive scheme were paid $1.00 for each 400 profit points they earned during the experiment. Participants in the *tournament* incentive scheme were paid a bonus of $46 if their total profit point performance for the 12 trials was in the top 10 percent, otherwise they received no compensation for their profit point performance.[11] The benchmark for determining the top 10 percent was based on performance in the individual sessions. The amount of the bonus equaled the average profit points compensation earned by participants in the individual condition, multiplied by 10. Thus, the expected value of the bonus in the tournament condition was the same as the average profit point compensation received by participants in the individual condition.[12] Because it was not possible to provide relative performance feedback based on all observations until all data had been collected, we ran the individual/no feedback condition first and, at the end of the session, provided these participants with feedback based on the performance of all participants in this condition. We next ran the individual/coarse feedback and individual/precise feedback conditions and based their feedback on performance in the individual/no feedback condition. Finally, we ran the tournament condition and based their feedback on the pooled data from the three individual conditions.

---

[9] We use performance rather than time as our dependent measure because the latter measures only the duration of effort whereas the former captures both the duration and the effectiveness of effort, which can be influenced by factors such as attention, strategy formation, and intensity (Bonner and Sprinkle 2002).

[10] On the initial quiz attempt, 87 percent of participants responded correctly to the pre-experiment question assessing knowledge of the common profit point potential for their reference group. The following message was displayed if the initial answer was incorrect: "Your overall profit points performance will be compared to other participants who have completed the same set of conditions as you. This means that the potential total profit points that could be earned is the same for you as for your reference group." The high percentage of correct initial responses together with the reinforcement provided to those participants who initially responded incorrectly indicates that participates were aware that the error term resulting from the state of nature was the same for all participants.

[11] Thus their only earnings would be the $5 show-up fee plus payment for any time points earned.

IV. RESULTS

Descriptive Statistics

Table 2 reports descriptive statistics and Figure 1 provides a graphical summary of these data. Panel A of Table 2 reports mean performance (cumulative profit points for the 12 trials) for each condition. These data suggest that participants in the individual condition performed better when they had coarse feedback relative to none, and their performance improved further with fine feedback. However, for participants in the tournament condition, feedback caused deterioration in performance. Performance was highest in the tournament condition when there was no feedback provided, and lowest when fine feedback was provided.

Table 2, Panel B reports mean change in performance, defined as profit points earned in the fourth quarter minus profit points earned in the first quarter. Recall that the states of nature were the same for the first and fourth quarters, and so this comparison is unaffected by noise in the common error. These data suggest that in the individual condition, feedback substantially increased performance for both coarse and fine feedback. However, in the tournament condition, relative performance feedback decreased performance for participants receiving fine feedback.

Hypotheses Tests

Taken together, our hypotheses predict an interaction between feedback and incentive scheme. Therefore, before reporting the planned comparisons to test the hypotheses, we report ANOVAs that test the full 3×2 model, using both performance and change in performance as the dependent variables. As reported in Table 3, Panel A, the interaction between feedback and incentive scheme is significant ($F = 3.62$, $p < 0.03$), when performance is the dependent variable. Likewise, as reported in Panel B, the feedback × incentive interaction is significant ($F = 10.98$, $p < 0.01$), when change in performance is the dependent variable. Figure 1 shows that these interactions are disordinal.

Formal tests of hypotheses are reported in Table 4.[13] Hypothesis 1a predicts that performance of participants compensated based on an individual incentive scheme will improve more when participants are provided with coarse feedback compared to no feedback about relative performance. Similarly, H1b predicts that performance of participants compensated based on an individual incentive scheme will improve more when participants are provided with fine feedback compared to no feedback about relative performance. As shown in Table 4, Panel A, while performance in the individual incentive scheme increased by 15.42 in the no feedback condition, it increased by 84.35 in the coarse condition ($t = 2.13$, $p < 0.02$, one-tailed) and 77.14 in the fine

---

[12] Although the tournament and individual incentive schemes have the same expected value at the start of the task (based on the probability of winning times the earning), the *perceived* expected values may differ because participants in the tournament scheme may perceive that their probability of winning is lower or higher depending on their initial levels of confidence.

[13] For simplicity and ease of interpretation, we report the results of t-tests. We also tested the within-contract analysis presented in Table 4 based on an analysis of simple effects and results were the same.

TABLE 2
Descriptive Statistics (Mean, {Standard Deviation}, n)

Panel A: Performance (Cumulative Profit Points)[a]

		Incentive Scheme[d]	
		a. Individual	**b. Tournament**
	1. None	1,766	2,230
		{599}	{374}
		n = 24	n = 22
Type of Relative Performance Feedback[c]	2. Coarse	1,863	2,050
		{566}	{571}
		n = 23	n = 22
	3. Fine	1,925	1,773
		{479}	{602}
		n = 21	n = 22

Panel B: Change in Performance (Q4 Profit Points − Q1 Profit Points)[b]

		Incentive Scheme	
		a. Individual	**b. Tournament**
	1. None	15.42	115.23
		{121.08}	{95.17}
		n = 24	n = 22
Type of Relative Performance Feedback	2. Coarse	84.35	92.27
		{99.06}	{140.13}
		n = 23	n = 22
	3. Fine	77.14	−41.59
		{66.53}	{121.22}
		n = 21	n = 22

---

[a] Performance is the cumulative profit points participants earned during the 12 trials.

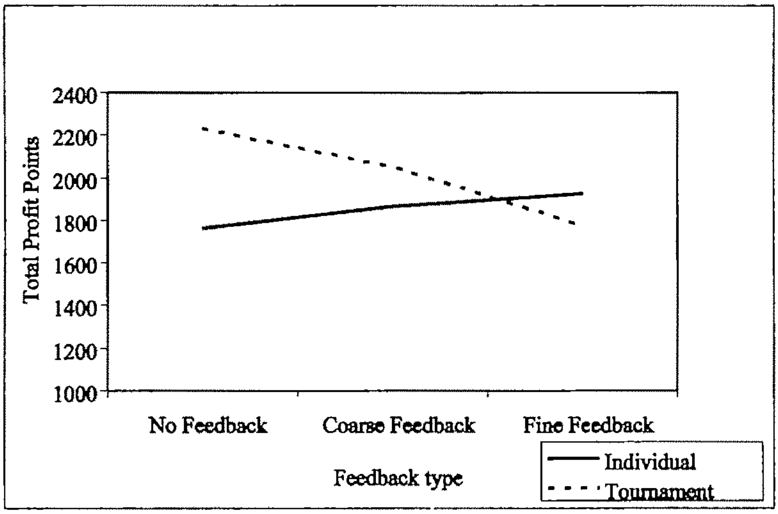
[b] Change in Performance is profit points earned in the last three trials (Q4) less profit points earned in the first three trials (Q1). The states of nature were the same in Q1 and Q4. Therefore, the potential profit points participants could earn in Q1 and Q4 is the same.

[c] Relative Performance Feedback was manipulated at three levels. Participants in the "None" condition received no relative performance feedback during the experiment. Participants in the "Coarse" condition received feedback at the end of Q1, Q2, Q3, and Q4 indicating whether their cumulative performance was above or below the 50th percentile of previous participants. Participants in the "Fine" condition received feedback at the end of Q1, Q2, Q3, and Q4 indicating how their cumulative performance ranked, in deciles, compared to previous participants.

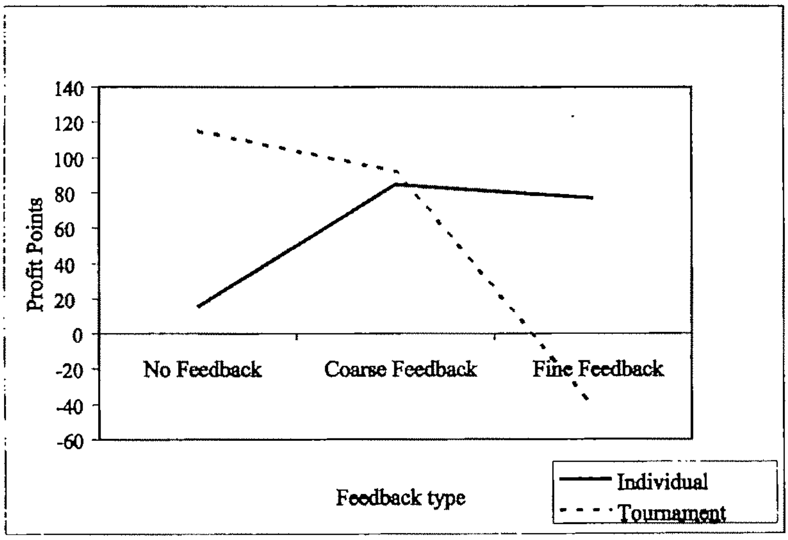
[d] Incentive Scheme was manipulated at two levels. Participants in the "Individual" condition received incentive pay that increased in profit points earned. Participants in the "Tournament" condition received a bonus if their cumulative profit points placed them in the top 10 percent compared to previous participants, otherwise they received zero incentive pay.

FIGURE 1
Summary of Results[a]

Panel A: Effect of Incentive Scheme and Feedback on Performance



Panel B: Effect of Incentive Scheme and Feedback on Change in Performance



---

[a] Variables are described in Table 2.

TABLE 3
ANOVA Results[a]

Panel A: Dependent Variable = Performance (Total profit points) (n = 134)

Source	df	Mean Square	F-Value	p-value
Feedback (None, Coarse, Fine)	2	257,111	0.883	0.42
Incentive Scheme (Individual, Tournament)	1	927,003	3.18	0.08
Feedback × Incentive Scheme	2	1,053,762	3.62	0.03

Panel B: Dependent Variable = Change in Performance (Q4 profit points – Q1 profit points) (n = 134)

Source	df	Mean Square	F-Value	p-value
Feedback (None, Coarse, Fine)	2	56,656	4.67	0.01
Incentive Scheme (Individual, Tournament)	1	449	0.037	0.85
Feedback × Incentive Scheme	2	133,236	10.98	<0.01

[a] Variables are described in Table 2.

condition ($t = 2.08$, $p < 0.02$, one-tailed). These results suggest that providing relative performance feedback increased performance of participants compensated based on an individual incentive scheme.

Although we made no prediction regarding the change in performance when participants in the individual incentive scheme condition received fine compared to coarse relative performance feedback, we test this comparison for completeness. There is no difference between means in the two conditions ($t = 0.28$, $p = 0.78$, two-tailed). Therefore, it appears that although the existence of relative performance feedback improved performance, the specific content of the feedback in terms of its precision had no additional effect.

The next set of hypotheses relate to comparisons within the tournament incentive scheme condition. Hypothesis 2a predicts that change in performance will not differ when coarse feedback is provided compared to providing no relative performance feedback. As reported in Table 4, Panel A, mean performance increased by 92.27 in the coarse and 115.23 in the none condition. These means are not significantly different ($t = 0.64$, $p = 0.53$, two-tailed), supporting H2a. Hypothesis 2b predicts that performance will improve to a lesser extent when fine feedback is provided compared to providing no relative performance feedback. This hypothesis is supported. Although mean performance increased by 115.23 in the no feedback condition, it decreased by 41.59 in the fine condition ($t = 4.77$, $p < 0.01$, one-tailed). Finally, H2c predicts that performance will improve less when fine feedback is provided compared to coarse feedback. This hypothesis is also supported. Specifically, mean performance increased in the coarse condition by 92.27, while it decreased in the fine condition by 41.59 ($t = 3.39$, $p < 0.01$, one-tailed).

Finally, we report tests of hypotheses related to the difference in performance and change in performance between the tournament and individual incentive scheme condition in the absence of relative performance feedback. Hypothesis 3a(b) predicts that in the absence of relative performance feedback, performance (change in performance) will be higher (improve more) in a

TABLE 4
Test of Hypotheses[a]

Panel A: Tests Comparing Relative Performance Feedback within Incentive Condition

Hypothesis	Mean Change in Performance: None	Coarse	Fine	Prediction	t- and p-values[b]	Conclusion
Individual Incentive Scheme						
H1a	15.42	84.35		Coarse > None	$t = 2.13$, $p < 0.02$	supported
H1b	15.42		77.14	Fine > None	$t = 2.08$, $p < 0.02$	supported
none		84.35	77.14	no prediction	$t = 0.28$, $p = 0.78$	
Tournament Incentive Scheme						
H2a	115.23	92.27		Coarse = None	$t = 0.64$, $p = 0.53$	supported
H2b	115.23		−41.59	Fine < None	$t = 4.77$, $p < 0.01$	supported
H2c		92.27	−41.59	Fine < Coarse	$t = 3.39$, $p < 0.01$	supported

Panel B: Tests Comparing Incentive Scheme in the Absence of Relative Performance Feedback

Hypothesis	Mean Performance or Change in Performance: Individual Incentive Scheme	Tournament Incentive Scheme	Prediction	t- and p-values[b]	Conclusion
H3a	1,766	2,230	Tournament > Individual	$t = 3.12$, $p < 0.01$	supported
H3b	15.42	115.23	Tournament > Individual	$t = 3.09$, $p < 0.01$	supported

---

[a] Variables are described in Table 2.

[b] p-values are one-tailed for directional, and two-tailed for non-directional predictions. Tests reported are two-sample t-tests; standard deviations and number of observations are reported in Table 2.

tournament compared to an individual incentive scheme. As shown in Table 4, Panel B, mean performance in the tournament condition is 2,230 compared to 1,766 in the individual condition, and this difference is statistically significant ($t = 3.12$, $p < 0.01$, one-tailed). Mean change in performance in the tournament condition is 115.23 compared to 15.42 in the individual condition. This difference is also statistically significant ($t = 3.09$, $p < 0.01$, one-tailed). Thus, both H3a and H3b are supported, indicating that in the absence of relative performance feedback, participants who received compensation based on a tournament incentive scheme not only performed better overall, but also improved their performance to a greater extent over time compared to participants who received compensation based on an individual incentive scheme.

The overall pattern of results suggests the following. Providing relative performance feedback to participants compensated under an individual incentive scheme *increases* performance regardless of the precision of the feedback. In contrast, providing relative performance feedback to participants compensated under a tournament incentive scheme *decreases* performance if the content is sufficiently precise for participants to assess their chances of winning the tournament. Otherwise relative performance feedback has no effect on performance. When no relative performance feedback is provided during the evaluation period, performance is higher in a tournament compared to an individual incentive scheme.

As a result of the disordinal interaction between incentive scheme and feedback, the tournament scheme loses its advantage when participants are provided with fine relative performance feedback. That is, as reported above, both performance and change in performance are greater in the tournament compared to individual condition when no feedback is provided. However, when fine feedback is provided, performance is no longer greater in the tournament condition (1,773 versus 1,925, for tournament and individual respectively, $t = 0.91$, $p = 0.37$, two-tailed). Moreover, the trend in performance is much worse in the tournament condition (−41.59 versus 77.14, $t = 3.95$, $p < 0.01$, two-tailed).

Supplemental Analysis

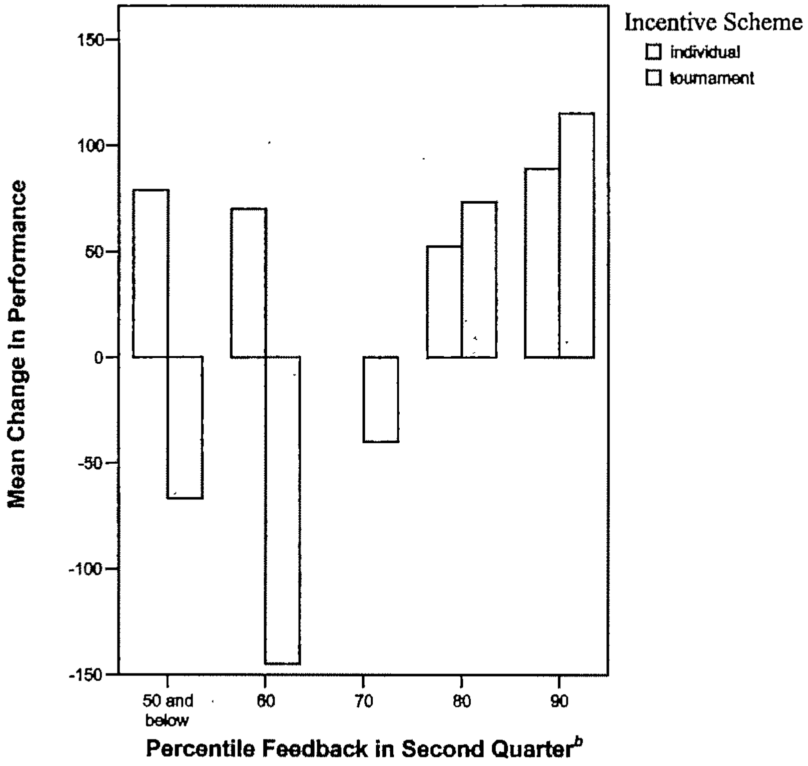
One potential explanation for performance differences across conditions is that participants were differentially motivated to view the trial history in order to acquire information for updating beliefs regarding the state of nature. It is likely that participants who opted to view the trial history would have a performance advantage. To assess whether this is the case, we ran the ANOVAs reported in Table 3 with total number of views included as an additional independent variable. As expected, total number of views has a significant main effect on performance ($F = 115.99$, $p < 0.001$), and change in performance ($F = 11.78$, $p < 0.01$). However, the feedback × incentive scheme interaction continues to be significant for both performance ($F = 3.73$, $p < 0.03$) and change in performance ($F = 16.59$, $p < 0.001$), indicating that the differences in performance are not due to differences in viewing behavior across conditions.

Our results suggest that while feedback improves performance regardless of its content in the individual condition, the effect of feedback depends on its content in the tournament condition. To further explore this relation, we examined change in performance conditional on the content of the feedback received by participants at the end of the second quarter (i.e., mid-way through the experiment). We restricted our analysis to participants receiving fine feedback, where the content is potentially informative. Figure 2 presents a histogram of mean change in performance conditional on second quarter feedback. As shown in Figure 2, mean performance increased for all feedback deciles in the individual condition. Moreover, the mean increase in the top two deciles (79.0) is the same as the bottom five deciles (78.6, $t = 0.01$, $p = 0.98$, two-tailed).[14] A different

---

[14] There was no participant in the individual incentive scheme whose second quarter feedback was in the 70th percentile.

FIGURE 2
Change in Performance Conditional on Feedback Received (Fine Feedback Condition)[a]



---

[a] Variables are described in Table 2.

[b] There was no participant in the individual incentive scheme condition whose second quarter feedback was in the 70th percentile.

picture emerges when the tournament condition is examined, however. Although mean performance increased for participants who received second-quarter feedback indicating they were in the top two deciles, mean performance decreased for the remaining deciles. In this condition, the difference between the highest two (83.8) and lowest five (−66.9) deciles is statistically significant ($t = 2.49$ $p < 0.04$, two-tailed). These results indicate that although the content of the feedback had little impact on future performance in the individual condition, the content made a dramatic impact in the tournament condition.

Additional analysis indicates that participants in the tournament/fine condition whose performance deteriorated did not reduce effort. Rather, their effort was less effective compared to participants whose performance improved. Specifically, a comparison of time spent (a proxy for effort) between participants whose performance deteriorated and those whose performance improved shows no difference in overall time ($p = 0.67$) or in fourth-quarter time ($p = 0.26$). Further, participants with improved performance, decreased the time spent in the fourth quarter compared to the first quarter by a much greater amount (49.6sec) on average compared to participants with deteriorated performance (7.7sec, $p < .05$, two-tailed). Another proxy for effort is the number of times participants viewed feedback within each trial. Comparisons of number of views overall, number of fourth quarter views and the change in views across the first and fourth quarters find no difference between participants whose performance improved and whose performance deteriorated. Taken together, these data indicate that the deteriorated performance was not due to a lower effort level. However, the data are consistent with reduced task strategy effectiveness. First, recall that the table provided to the participants contained 11 dominated choices. Because the expected value of a dominated choice is clearly lower than an alternative choice, selection of a dominated choice is evidence of an ineffective task strategy. Compared to participants with improved performance, participants with deteriorated performance made more dominated choices overall (23.0 versus 36.2, $p < 0.03$ two-tailed), and in the fourth quarter (4.7 versus 10.4, $p < 0.01$, two-tailed), and their learning to avoid making dominated choices lagged (comparing the fourth to first quarters, -3.0 compared to $+2.1$, $p < 0.01$, two-tailed). Second, if participants settle on a strategy, then they are likely to make the same choice for the first period within each trial. A comparison of the standard deviation of first period choices shows more variation for participants whose performance deteriorated (standard deviation 2.2 for improved, 3.9 for deteriorated, $p < 0.02$, two-tailed), suggesting a continued search for a strategy throughout the experiment.

Taken together, these results suggest that participants' deteriorating performance is not the result of reduced effort but rather because of factors such as devoting cognitive effort to activities unrelated to task strategy (e.g., interpreting the meaning of the relative performance feedback, evaluating their chances of obtaining the bonus, or worrying about their performance), which hampered their performance (Kanfer and Ackerman 1989), or adopting a risky strategy in the hope of catching up (Camerer and Hogarth 1999). Some evidence in support of this explanation is also provided in the responses to the post-experimental questionnaire, which show that relative to participants in the individual condition, tournament participants thought more about their rank ($p < 0.01$), were more nervous about their rank ($p < 0.03$), and perceived that thinking about their rank interfered with their performance ($p < 0.01$).

Finally, we conducted separate analysis for each quarter via a 3 (feedback) × 2 (incentive scheme) ANOVA. This analysis shows that participants in the tournament incentive scheme had significantly higher performance in the first quarter, consistent with the incentive effects predicted by economic theory. The feedback × incentive scheme interaction was not significant in the first quarter, which is expected given that relative performance feedback was first received after the first quarter. However, a significant interaction emerges in the second quarter and remains in the third and fourth quarters. Thus, the effects of relative performance feedback on performance did not fade out as participants obtained more experience on the task. In fact, the differential effects of relative performance feedback for the tournament versus individual incentive scheme became more pronounced.

V. CONCLUSIONS

Firms routinely use tournament-based compensation schemes where the compensation of the manager is based on performance relative to others. At the same time, compensation plans for which a manager's pay depends only on his own performance are also prevalent in practice. In this paper we examine the effect of providing relative performance feedback when participants are compensated under one of these types of compensation schemes.

We find that providing relative performance feedback increases the performance of participants who are compensated based on an individual incentive scheme. Moreover, the specific content of the feedback has no impact on performance: participants increase performance to the same extent when receiving coarse or fine feedback and this increase in performance is not affected by whether the feedback indicates that relative performance lags or excels.

Providing relative performance feedback has the opposite effect for participants compensated under a tournament incentive scheme. Providing coarse feedback has no effect on mean performance. However, providing fine feedback causes mean performance to deteriorate. This deterioration is caused by participants' response to the content of the feedback. Performance deteriorates for those participants whose feedback indicates their performance lags, which represents a majority of the participants. Although performance increases for those participants whose feedback indicates their performance excels, this increase is not sufficient to overcome the deterioration in performance of the other participants, resulting in a net decrease overall. Interestingly, supplemental analysis suggests that the deteriorating performance is not due to reduced effort but rather to reduced effectiveness of the participants' task strategy as they devote cognitive resources to activities unrelated to the task and/or adopt more high-risk strategies.

Our study has several implications for the design of compensation schemes, performance measurement systems, and reporting systems in firms. Our study implies that the usefulness of relative performance feedback depends on the type of incentive scheme. Whereas providing relative performance feedback is likely to have positive consequences when managers are compensated via an individual incentive scheme, such feedback is likely to have negative consequences when managers are compensated via a tournament incentive scheme. Thus, our study suggests that organizations should distribute relative performance feedback when using individual schemes but withhold such information when using tournament schemes. The latter case may be especially challenging for organizations if the relative information is routinely provided in its accounting systems or if employees are not willing to accept contracts that provide no relative performance feedback. However, in many organizations an individual's performance and bonus information is kept confidential from other individuals and tournaments are often used in recruitment and promotion processes where participants may have knowledge of who is competing, but not the relative ranks.

Our study also implies that in settings where relative performance feedback is not revealed, a tournament incentive scheme results in higher performance than an individual scheme. However, numerous other potential costs and benefits need to be considered when evaluating whether to adopt and the specific design of a tournament compensation scheme. For example, tournaments may motivate managers to make more risky decisions, which may or may not be beneficial to the firm (Chow and Haddad 1991; Sayre et al.1998). The effectiveness of tournaments may be undermined by motivating collusion (Bandiera et al. 2005), discouraging innovation, hindering cooperation, or, as our study finds, reducing performance of lagging managers. The choice of an improper reference group (Gibbons and Murphy 1990) may also decrease the effectiveness of tournaments. Tournaments may also encourage gamesmanship due to the kink in incentive pay such schemes create (Jensen 2001). On the other hand, tournaments may provide additional benefits such as sorting on attributes the firm finds desirable (Sprinkle 2003), less need for costly monitoring (Henderson and Fredrickson 2001), and increased flexibility, especially in the presence of environmental uncertainty (Nalebuff and Stiglitz 1983).

While a *BusinessWeek* survey reveals that one-third of U.S. corporations use tournament-based incentive schemes, it also reports that companies are re-evaluating these schemes (McGregor 2006). Our study demonstrates that designing an incentive compensation plan and reporting system that is effective and efficient in motivating performance that benefits the firm is no easy task. Numerous variables may impact its effectiveness and even interact with each other. Thus, constant re-evaluation of the effectiveness of incentive compensation schemes and reporting systems is warranted. A logical next step for future research is to investigate the effectiveness of providing relative performance feedback using a hybrid incentive scheme containing both tournament and individual components, or using a tournament scheme with more graduated payments rather than the "winner take all" approach used in our study.

REFERENCES

Antle, R., and A. Smith. 1986. An empirical investigation of the relative performance evaluation of corporate executives. *Journal of Accounting Research* 24 (1): 1–39.

Atkinson, A. A., R. Banker, R. S. Kaplan, and S. M. Young. 2001. *Management Accounting*. 3rd edition. Upper Saddle River, NJ: Prentice Hall.

Bandiera, O., I. Barankay, and I. Rasul. 2005. Social preferences and the response to incentives: Evidence from personnel data. *The Quarterly Journal of Economics* 120 (3): 917–962.

Bandura, A. 1991. Social cognitive theory of self regulation. *Organizational Behavior and Human Decision Processes* 50 (2): 248–287.

Banker, R. D., and S. M. Datar. 1989. Sensitivity, precision, and linear aggregation of signals for performance evaluation. *Journal of Accounting Research* 27 (1): 21–39.

Bonner, S. E., R. Hastie, G. B. Sprinkle, and S. M. Young. 2000. A review of the effects of financial incentives on performance in laboratory tasks: Implications for management accounting. *Journal of Management Accounting Research* 12 (1): 19–64.

———, and G. B. Sprinkle. 2002. The effects of monetary incentives on effort and task performance: Theories, evidence, and a framework for research. *Accounting, Organizations and Society* 27 (4–5): 303–345.

Bull, C., A. Schotter, and K. Weigelt. 1987. Tournaments and piece rates: An experimental study. *The Journal of Political Economy* 95 (1): 1–33.

Bushman, R. M., and A. J. Smith. 2001. Financial accounting and corporate governance. *Journal of Accounting and Economics* 32 (1-3): 237–333.

Camerer, C. F., and R. M. Hogarth. 1999. The effects of financial incentives in experiments: A review and capital-labor-production framework. *Journal of Risk and Uncertainty* 19 (1/3): 7–42.

Casas-Arce, P., and F. Martinez-Jerez. 2007. Relative performance compensation and dynamic incentives. Working paper, University of Oxford.

Chow, C. W., and K. M. Haddad. 1991. Relative performance evaluation and risk taking in delegated investment decisions. *Decision Sciences* 22 (3): 583–593.

Cooper, R., R. S. Kaplan, L. S. Maisel, E. Morrissey, and R. M. Oehm. 1992. *Implementing Activity-Based Cost Management: Moving from Analysis to Action*. Montvale, NJ: Institute of Management Accountants.

———, and ———. 1998. The promise—and peril—of integrated cost systems. *Harvard Business Review* 76 (4): 109–119.

Feltham, G. A., and J. Xie. 1994. Performance measure congruity and diversity in multi-task principal/agent relations. *The Accounting Review* 69 (3): 429–453.

Festinger, L. 1954. A theory of social comparison processes. *Human Relations* 7: 117–140.

Frederickson, J. R. 1992. Relative performance information: The effects of common uncertainty and contract type on agent effort. *The Accounting Review* 67 (4): 647–669.

Gibbons, R., and K. J. Murphy. 1990. Relative performance evaluations for chief executive officers. *Industrial Labor Relations Review* 43 (3): 30S–51.

———. 1998. Incentives in organizations. *The Journal of Economic Perspectives* 12 (4): 115–132.

Henderson, A. D., and J. W. Fredrickson. 2001. Top management team coordination needs and the CEO pay gap: A competitive test of economic and behavioral views. *Academy of Management Journal* 44 (1): 96–117.

Holmstrom, B. 1979. Moral hazard and observability. *The Bell Journal of Economics* 10 (1): 74–91.

Indjejikian, R. J. 1999. Performance evaluation and compensation research: An agency perspective. *Accounting Horizons* 13 (2): 147–157.

Jensen, M. C., and K. J. Murphy. 1990. Performance pay and top-management incentives. *The Journal of Political Economy* 98 (2): 225–264.

———. 2001. Corporate budgeting is broken—Let's fix it. *Harvard Business Review* 79 (10): 94–101.

Kanfer, R., and P. Ackerman. 1989. Motivation and cognitive abilities: An integrative/aptitude-treatment interaction approach to skill acquisition. *The Journal of Applied Psychology* 74 (4): 657–690.

Kessler, L., and R. H. Ashton. 1981. Feedback and prediction achievement in financial analysis. *Journal of Accounting Research* 19 (1): 146–162.

Kluger, A. N., and A. DeNisi. 1996. The effects of feedback interventions on performance: A historical review, a meta-analysis, and a preliminary feedback intervention theory. *Psychological Bulletin* 119 (2): 254–284.

Lambert, R., D. Larcker, and K. Weigelt. 1993. The structure of organizational incentives. *Administrative Science Quarterly* 38 (3): 438–461.

Lazear, E. P., and S. Rosen. 1981. Rank-order tournaments as optimum labor contracts. *The Journal of Political Economy* 89 (5): 841–864.

Locke, E. A., and G. P. Latham. 1990. *A Theory of Goal Setting and Task Performance*. Englewood Cliffs, NJ: Prentice Hall.

Matsumura, E. M., and J. Y. Shin. 2006. An empirical analysis of an incentive plan with relative performance measures: Evidence from a postal service. *The Accounting Review* 81 (3): 533–567.

McGregor, J. 2006. The struggle to measure performance. *BusinessWeek* (January 9): 26–28.

Muller, W., and A. Schotter. 2003. Workaholics and drop outs in optimal organizations. Mimeo, New York University, New York.

Murphy, K. 1999. Executive compensation. In *Handbook of Labor Economics*, Vol 3b, edited by O. Ashenfelter and D. Card. North Holland, Amsterdam: Elsevier.

Nalebuff, B. J., and J. E. Stiglitz. 1983. Prizes and incentives: Towards a general theory of compensation and competition. *The Bell Journal of Economics* 14 (1): 21–43.

O'Keefe, M., W. K. Viscusi, and R. J. Zeckhauser. 1984. Economic contests: Comparative reward schemes. *Journal of Labor Economics* 2 (1): 27–56.

O'Reilly, C., B. Main, and G. Crystal. 1988. CEO compensation as tournament and social comparison: A tale of two theories. *Administrative Science Quarterly* 33: 257–274.

Prendergast, C. 1999. The provision of incentives in firms. *Journal of Economic Literature* 37 (1): 7–63.

Sayre, T. L., F. W. Rankin, and N. L. Fargher. 1998. The effects of promotion incentives on delegated investment decisions: A note. *Journal of Management Accounting Research* 10: 313–323.

Sprinkle, G. B. 2000. The effect of incentive contracts on learning and performance. *The Accounting Review* 75 (3): 299–326.

———. 2003. Perspectives on experimental research in managerial accounting. *Accounting, Organizations and Society* 28 (2-3): 287–318.

Tesser, A., and J. Campbell. 1980. Self-definition: The impact of the relative performance and similarity of others. *Social Psychology Quarterly* 43: 341–347.

Young, S. M., J. Fisher, and T. M. Lindquist. 1993. The effect of intergroup competition and intragroup cooperation on slack and output in a manufacturing setting. *The Accounting Reviews* 68 (3): 466–481.

THE ACCOUNTING REVIEW
Vol. 83, No. 4
2008
pp. 915–956

American Accounting Association
DOI: 10.2308/accr.2008.83.4.915

The Effects of Financial Statement and Informational Complexity on Analysts' Cash Flow Forecasts

Leslie Hodder
Indiana University

Patrick E. Hopkins
Indiana University

David A. Wood
Brigham Young University and Indiana University

ABSTRACT: We characterize the operating-activities section of the indirect-approach statement of cash flows as backward because it presents reconciling adjustments in a way that is opposite from the intuitively appealing, future-oriented, Conceptual Framework definitions of assets, liabilities, and the accruals process. We propose that the reversed-accruals orientation required in the currently mandated indirect-approach statement of cash flows is unnecessarily complex, causing information-processing problems that result in increased cash flow forecast error and dispersion. We also predict that the mixed pattern (i.e., +/−, −/+) of operating cash flows and operating accruals reported by most companies impedes investors' ability to learn the time-series properties of cash flows and accruals. We conduct a carefully controlled experiment and find that (1) cash flow forecasts have lower forecast error and dispersion when the indirect-approach statement of cash flows starts with operating cash flows and adds changes in accruals to arrive at net income and (2) cash flow forecasts have lower forecast error and dispersion when the cash flows and accruals are of the same sign (i.e., +/+, −/−); with the sign-based difference attenuated in the forward-oriented statement of cash flows. We also conduct a quasi-experiment to test our mixed-sign versus same-sign hypotheses using archival samples of publicly available I/B/E/S and Value Line cash flow forecasts. We find that the passively observed samples of cash

---

We thank Mary Barth and Katherine Schipper for their suggestions during the development of this project and Kris Allee, Rob Bloomfield, Shana Clor-Proell, Vicki Dickinson, Susan Keenan, Reuven Lehavy, Bob Libby, Laureen Maines, Mark Nelson, Derek Oler, Kenny Reynolds, Mike Staub, Mike Tiller, participants at the IAAER Reporting Financial Performance workshops in Bordeaux and New York City, and participants in the workshops at Cornell University, the University of Florida, Indiana University, New York University, the 2007 University of Utah Winter Accounting Conference, and the 10th World Congress of Accounting Educators in Istanbul, Turkey for their comments. We thank the International Association for Accounting Education and Research (IAAER) and the KPMG and University of Illinois Business Measurement Research Program for their generous research support. This project also benefited from funding provided by the Kelley School of Business and BKD LLP and the research assistance of Yvonne Lee.

Editor's note: This paper was accepted by Mark W. Nelson.

Submitted: January 2007
Accepted: November 2007
Published Online: July 2008

flow forecasts exhibit a similar pattern of mixed-sign versus same-sign forecast error as documented in our experiment.

Keywords: *statement of cash flows; cash flow forecasts; forecast errors; forecast dispersion.*

Data Availability: *Contact the authors.*

I. INTRODUCTION

In this study, we investigate whether the currently required structure of the operating-activities section of the indirect-approach statement of cash flows impedes investors' ability to learn the time-series properties of operating cash flows and operating accruals. We propose that the current structure of the indirect-approach statement of cash flows, which starts with reported earnings and *reverses* changes in non-cash and non-operating items to arrive at operating cash flows, presents information in a way that is opposite of the intuitive, future-oriented perspective taken in the Conceptual Framework definitions of assets (FASB 1985, para. 25), liabilities (para. 35), and the accruals process (para. 141). Prior research suggests that information presentation that does not conform to the semantic, sequential, or causal structure of a data-generation process can negatively influence humans' ability to learn the forecast-relevant parameters of that process (Luft and Shields 2001). Thus, we predict that the "reverse-process" format, currently required in the indirect-approach statement of cash flows, interferes with financial statement users' learning, resulting in systematically higher cash flow forecast errors and greater forecast dispersion.

We also investigate whether the offsetting (i.e., "mixed sign") pattern of operating cash flows and operating accruals information reported by many companies also impedes investors' ability to learn the time-series properties of operating cash flows and operating accruals. Prior research suggests that this offsetting pattern of positive and negative forecast-model inputs will likely lead to increased incidence of forecast errors over the errors observed for same-sign inputs. Overall, we predict that same-sign operating cash flows and operating accruals information will result in lower forecast errors and dispersion than mixed-sign operating cash flows and operating accruals information. However, consistent with our format-related predictions, we expect that presenting cash flow and operating-accruals-change information in a more accruals-process-congruent (i.e., "forward") format will result in improved learning of the model parameters, causing lower forecast errors and dispersion.

We test these predictions in a computerized experiment in which 50 second-year business graduate students, with prior training in financial forecasting and residual-income valuation models, sequentially forecast year-two cash flows from operations (CFO) for 16 different companies after receiving year-one CFO and year-one changes in non-cash, current net operating assets (to help exposition, we refer to this change as $CNOA$). After *each* of the 16 judgments, we provide participants with *cumulative* feedback including the inputs to their forecast tasks (i.e., year-one CFO and $CNOA$ for each preceding forecast) and accuracy-related information for each preceding forecast (i.e., the matched set of "actual" year-two CFO, their forecasts of year-two CFO, and the percentage forecast error). For each of the companies, we provide half of the participants with highly summarized indirect-approach statement of cash flows information in the currently mandated *reverse*-order format (i.e., net income $-$ $CNOA = CFO$), and we provide the other half with the same information in *forward*-order (i.e., $CFO + CNOA = NI$).

We also counterbalance the signs of the year-one CFO and $CNOA$ information, so that each subject receives each of the following year-one CFO / $CNOA$ sign combinations four times: $+/+$,

+/−, −/+, −/−.[1] This counterbalanced design highlights an important advantage of experiments as a research approach: experimenter control (Libby et al. 2002). In the present study, we are able to evenly distribute the four possible patterns of cash flows and accruals. As a result, we investigate important conditions that are under-represented in published, real-world financial statements.

Consistent with our predictions, we find that the underlying structure of the operating section of the indirect-approach statement of cash flows significantly affects the extent to which participants learn the time-series model that generates year-two *CFO*. Compared to the forward-order format for the indirect-approach statement of cash flows, we find that forecast errors and forecast dispersion are significantly higher under the currently mandated reverse-order format. In addition, we find that mixed-sign forecast inputs lead to significantly higher cash flow forecast errors and forecast dispersion across both forecast conditions, but that the forecast errors from the mixed-sign inputs are greatest in the currently mandated reverse-order indirect-approach statement of cash flows.

In recent years, financial analysts have published forecasts of *CFO* with increasing frequency (DeFond and Hung 2003). Motivated by our theoretical development and experimental findings, we also conduct a quasi-experimental analysis designed to determine whether analysts' published *CFO* forecasts exhibit a pattern of forecast errors that is consistent with the errors observed in our experiment. Because all U.S. publicly traded non-real-estate and nonfinancial companies must prepare reverse-order indirect-approach statements of cash flows, we cannot test with archival data whether the forward-order indirect-approach statement of cash flows yields lower forecast errors.[2] However, publicly available *CFO* and *CNOA* data exhibit sufficient variability to allow a quasi-experimental test of our mixed-sign hypotheses. As we predict, after controlling for economic factors previously associated with analysts' forecast accuracy, we find that our separate analyses of I/B/E/S and Value Line *CFO* forecasts exhibit significantly higher year-two forecast errors when year-one *CFO* and year-one *CNOA* have mixed signs (i.e., +/−, −/+ versus +/+, −/−).

Although we focus on cash flow forecasts, our study is related to prior research suggesting that analysts and investors systematically ignore forecast-relevant information contained in publicly released performance statements (i.e., statements of income and of cash flows). For example, Elgers et al. (2003) and Bradshaw et al. (2001) provide evidence that sell-side analysts' earnings forecasts do not sufficiently reflect the transitory nature of current-period accruals, resulting in predictable patterns of earnings-forecast errors. These studies demonstrate that current-period analysts' earnings-forecast errors are positively related to prior-period earnings accruals (i.e., difference between operating cash flows and earnings). Overall, these results are consistent with financial statement users' systematic information-processing inefficiency when combining two types of performance information (i.e., cash flow and accruals) contained in the statements of cash flows for publicly listed U.S. companies.

Our experimental results suggest that two features of the indirect-approach statement of cash flows reporting regime—financial statement structure and information configuration—can significantly affect financial statement users' ability to detect time-series patterns in reported accounting information. The conceptual frameworks of the United States' Financial Accounting Standards

---

[1] We also counterbalance the order of the companies by rotating the companies and by reversing each of the rotated orders. This counterbalancing scheme controls for order effects and also results in all of the companies appearing with equal frequency across the 16-company forecast sequence.

[2] Statement of Financial Accounting Standards (SFAS) No. 95 (FASB 1987) allows companies to prepare the statement of cash flows using the (1) indirect approach or (2) the direct approach with indirect-approach information also reported. Thus, some form of the accruals-based–income-to-cash flows reconciliation in the indirect approach is provided by all companies. According to the American Institute of Certified Public Accountants (AICPA 2005), 592 out of 600 companies (98.7 percent) report cash flows from operations only using the indirect approach.

Board (FASB) and the International Accounting Standards Board (IASB) identify understandability as a necessary qualitative characteristic of financial information. Financial statement structures that are more understandable should increase comprehension of the time-series properties (e.g., persistence) of reported performance information, leading to higher-quality financial forecasts.

Whether understandability is improved through economy-wide reformatting of the primary financial statements (e.g., SFAS No. 130, FASB 1997) or via user-level decision aids (cf., Bonner 1999) depends on the perceived costs and benefits of each. Our analysis provides evidence on a potential benefit of mandated statement reformatting (i.e., improved investor understanding of time-series properties of performance measures). Asset pricing theory indicates that market efficiency increases as the level of available information increases and as investor knowledge becomes more homogenous (Easley and O'Hara 2004). Thus, financial disclosure that is equally accessible to more- and less-sophisticated investors can increase market efficiency, even if the number of value-relevant facts reported in the financial statements is unchanged.

We organize the remaining paper in the following way. In the next section, we discuss current cash flow reporting and, after considering relevant judgment and decision-making research, make our research predictions. We describe our experiment and results in Sections III and IV. We describe our quasi-experimental analysis of I/B/E/S and Value Line cash flow forecasts in Section V and provide a summary and conclusion in Section VI.

II. THEORY AND PREDICTIONS

Financial statement analysis and forecasting is an iterative, evaluative process through which financial statement users engage in information discovery, expectation formation, hypothesis testing, and conditional prediction. During this process, financial statement users attempt to understand patterns and relations in reported company-specific information, often with the goal of identifying the portion of performance that is expected to recur in future periods. Prior research suggests that the format of information presented in financial statements can influence the way company-specific information is processed and used by novices (e.g., Maines and McDaniel 2000) and experts (e.g., Hirst et al. 2004). Thus, financial statement format also likely affects financial statement users' time-series-pattern learning and resulting financial-forecasting judgments.

An important structural feature of the currently prescribed format for the indirect-approach statement of cash flows is its "reverse" orientation; that is, increases in *CNOA* are reversed to reconcile current-period earnings to current-period *CFO*. For example, an increase in an operating asset account, such as accounts receivable, is subtracted from earnings to arrive at *CFO*. Likewise, an increase in an operating liability account, such as accounts payable, is added to earnings to arrive at *CFO*. However, the valence of each of these adjustments is opposite (i.e., reverse) from the conditional expected future cash-flow effects of each item (i.e., compared to current period *CFO*, we expect additional future cash flows for increasing accounts receivable balances and additional future cash outflows for increasing accounts payable balances). Indeed, the logic underlying the operating-section adjustments in the indirect-approach statement of cash flows occasionally leads our most gifted teaching colleagues to implore confused students and executives to simply memorize the reverse relation because the reverse-accruals logic is difficult.[3]

As modeled in Dechow et al. (1998), Barth, Cram, and Nelson (2001), and Francis and Smith (2005), current-period *CNOA* (i.e., "current-period accruals") are positively associated with future cash flows. The *positive*, intertemporally dependent relation between current-period accruals and future cash flows conforms to the accrual-accounting perspective offered in most introductory and intermediate accounting courses (e.g., Phillips et al. 2005; Revsine et al. 2005) and provides an intuitive and parsimonious explanation for the empirical observation that current period earnings (which includes the current-period *CNOA*) explain more variation in next period's operating cash flows than current-period operating cash flows (Dechow et al. 1998; Barth, Cram, and Nelson 2001). Further, the definitions of assets and liabilities in Statement of Financial Accounting Concepts No. 6 (FASB 1985) suggest that the relation between current-period change in operating accruals and future cash flows is positive and causal.

---

[3] The sample of popular, financial accounting books we reviewed often provide little discussion of accruals-process-congruent future-period cash flow effects, and instead offer highly detailed comprehensive lists of the operating net asset accounts along with individual instructions for whether an increase or decrease in each account is added to, or subtracted from, earnings to arrive at *CFO*.

Psychology research offers some insights into the likely effects of reverse-presentation of information in financial-information comprehension and performance-forecasting tasks. At its most basic level, the process of using financial statements to forecast future performance is one in which financial statement users learn probabilistic relations between dependent and independent variables and make out-of-sample predictions of a future-value-correlated measure, such as future earnings or operating cash flows. A robust finding in prior psychology research is that learning and subsequent judgment accuracy are greater for prediction scenarios with a positive relation between independent and dependent variables than for prediction scenarios with a statistically equivalent negative relation (Naylor and Clark 1968; Deane et al. 1972; Brehmer 1973, 1974, 1979; Brehmer et al. 1974).

Interestingly, positive relations (e.g., $y = a + bx$) in multiple-cue probabilistic learning tasks result in superior learning and judgment performance for tasks in which individuals have no prior knowledge of the signs of the model parameters (i.e., they must learn the sign and weight of parameters based solely on the data) *and* for tasks in which individuals are provided with pre-experiment information about the signs of the parameters. Although, Muchinsky and Dudycha (1975) and Sniezek (1986) provide some evidence that learning and judgment accuracy improve in context-specific tasks with labeled variables, the settings in which prior research demonstrates improved negative-relation learning are fairly straight-forward (e.g., predicting college grades based on high school grades in related and unrelated subjects).

Although these context-related findings provide some support for financial statement users having the ability to adjust for the negative-accruals presentation format in the indirect-approach statement of cash flows, we believe the use of cash flow and accruals information in forecasting is sufficiently complex to mitigate the potential benefits of contextual familiarity. Thus, we propose that the currently implemented indirect-approach structure for the statement of cash flows will impede learning of persistence of the *CFO* and *CNOA* components of year-one earnings, leading to higher levels of year-two forecast errors and higher levels of year-two forecast dispersion. More formally, we propose the following hypotheses (in alternative form):

H1a: Investors' year-two operating cash flow forecast errors will be higher when increases (decreases) in year-one operating net assets are presented as negative (positive) reconciling items in an earnings-to-cash flows reconciliation, as compared to the opposite presentation in a cash flows-to-earnings presentation.

H1b: Investors' year-two operating cash flow forecast dispersion will be higher when increases (decreases) in year-one operating net assets are presented as negative (positive) reconciling items in an earnings-to-cash flows reconciliation, as compared to the opposite presentation in a cash flows-to-earnings presentation.

Prior research also suggests that *CFO* and *CNOA* have a +/− "mixed sign" configuration, on average. For example, Dechow et al. (1998) report average values of approximately 1.63 per share for *CFO* and −0.50 per share for *CNOA*, while Sloan (1996) reports this configuration for 7 out of 10 deciles. Given the cognitive complexity of learning a historical trend of year-one *CFO*, year-one *CNOA*, and year-two *CFO*, and of forecasting out-of-sample *CFO*, we propose that mixed-sign variation in model inputs will further overload the processing capacity of individuals. In particular, humans quickly reach computational capacity in complex tasks (such as trend learning), leaving little additional mental capacity for manipulation of data or complex calculations (Miller 1956). Further, even in high-stakes, real-world settings (e.g., investing), individuals will attempt to use schematic problem representations and take computational shortcuts (Hong et al. 2007; Simon 1982). This leads us to the following (alternative form) predictions about the effect of mixed-sign versus same-sign inputs into cash flow forecasts.

H2a: Compared to forecasts made when year-one changes in operating net assets and year-one operating cash flows have the same sign, investors' year-two operating cash flow forecast errors will be higher when year-one changes in operating net assets and year-one operating cash flows have different signs.

H2b: Compared to forecasts made when year-one changes in operating net assets and year-one operating cash flows have the same sign, investors' year-two operating cash flow forecast dispersion will be higher when year-one changes in operating net assets and year-one operating cash flows have different signs.

III. EXPERIMENTAL DESIGN

We investigate the effects of cash-flow statement format and forecast-relevant information configuration (i.e., sign of model inputs) in a 2 × 2 mixed-design experiment (format is the between-subjects factor varied at two levels: forward versus reverse; sign is the within-subjects factor varied at two levels: mixed- versus same). 50 second-year master's-level business students participated in our experiment.

Master's-level business students are appropriate participants for two reasons. First, our theory and hypotheses are related to a general psychology of inference and pattern learning in a financial-forecasting setting. Because we have no *ex ante* reason to believe that general forecasting experience will eliminate the effects of format or input-sign configuration on forecast accuracy or dispersion, we decided to avoid unnecessarily consuming limited available analyst resources. Second, Elliott et al. (2007) find that second-year master's students (i.e., similar to our participants) are suitable proxies for nonprofessional investors, an important constituent group for accounting standard setters and regulators.

As indicated in Table 1, participants previously completed 10 (standard deviation = 4) accounting and finance courses, with one of those courses a three-credit hour M.B.A.-level financial statement analysis course that included an emphasis on residual-income valuation and financial forecasting. Participants had, on average, 14.5 (standard deviation = 30) months of prior work experience. As indicated in Table 1, we find no significant differences (all two-tailed p-values >0.10) between treatment groups for demographic information, including current degree program, prior work experience, accounting/finance classes taken, the number of participants who plan to buy or sell equity securities, or the number of times participants previously performed fundamental analysis on the financial information of publicly traded companies.[4] Overall, our participants appear to be knowledgeable about the relation between cash flows and accrual accounting and have experience in financial forecasting.

---

[4] We present a subset of demographic information in Table 1. None of the demographic questions (tabulated and untabulated) yield significant differences across treatment conditions (all two-tailed p-values >0.10).

TABLE 1

Summary of Demographic Information and Pre- and Post-Experiment Participant Assessments

Panel A: Demographic Information[b]

	Format[c]		
	RO (n = 25)	**FO (n = 25)**	**Comparison**[a]
Number pursuing M.B.A. degree (versus M.P.A.)	19	19	$\chi^2 = 0.00$
Mean months work experience	10	19	$Z = 0.95$
Mean courses in finance and accounting	10	10	$Z = 0.04$
Number who plan to buy or sell stock in future	22	23	$\chi^2 = 0.22$
Times performed fundamental analysis on public data			$\chi^2 = 4.34$
Category detail:			
Once	2	2	
Once to five times	10	14	
Six to ten times	5	6	
More than ten times	8	2	

Panel B: Pre-Experiment Items[d]

	Format[c]		
	RO (n = 25)	**FO (n = 25)**	**Comparison**[a]
Accounting question 1 correct in first attempt	25	23	$\chi^2 = 2.08$
Perceived difficulty of accounting question 1	4.00	3.84	$Z = -0.73$
Accounting question 2 correct in first attempt	20	21	$\chi^2 = 0.14$
Perceived difficulty of accounting question 2	5.64	4.96	$Z = -0.95$

Panel C: Post-Experiment Items[e]

	Format[c]		
	RO (n = 25)	**FO (n = 25)**	**Comparison**[a]
Difficulty of forecasting task in experiment	8.16	8.68	$Z = 0.55$
Confidence in forecasts made in experiment	6.96	7.40	$Z = 0.55$

---

[a] None of the comparisons are statistically significant. Comparisons of categorical (i.e., frequency) data incorporate χ^2 tests. Comparisons of interval data incorporate Wilcoxon/Mann-Whitney tests (Conover 1999, 271-286). Parametric-comparisons yield a similar pattern of insignificant differences between groups.

(continued on next page)

TABLE 1 (continued)

[b] After all forecasting-related questions, we presented participants with a series of demographic questions.

[c] RO = reverse-order condition, FO = forward-order condition.

[d] Results of two accounting questions posed to all participants. We provide data for the number of participants who correctly answered each question in their first attempt, along with the perceived difficulty of each question. The difficulty scale ranged from 1 (Not at all Difficult) to 15 (Extremely Difficult). The first question required participants to determine cash flows from customer sales given a set of facts related to sales and accounts receivable. The second question required participants to determine cash flows from operations given a hypothetical company's operating earnings and beginning and ending balances for receivables, inventories, and payables.

[e] Participants' difficulty assessment for the cash flow forecasting task presented to them in the experiment. Post-Experiment Confidence Score = Participants confidence assessment for the cash flow forecasting task presented to them in the experiment. The scale ranged from 1 (Not at all Confident) to 15 (Extremely Confident).

Procedure for Experiment

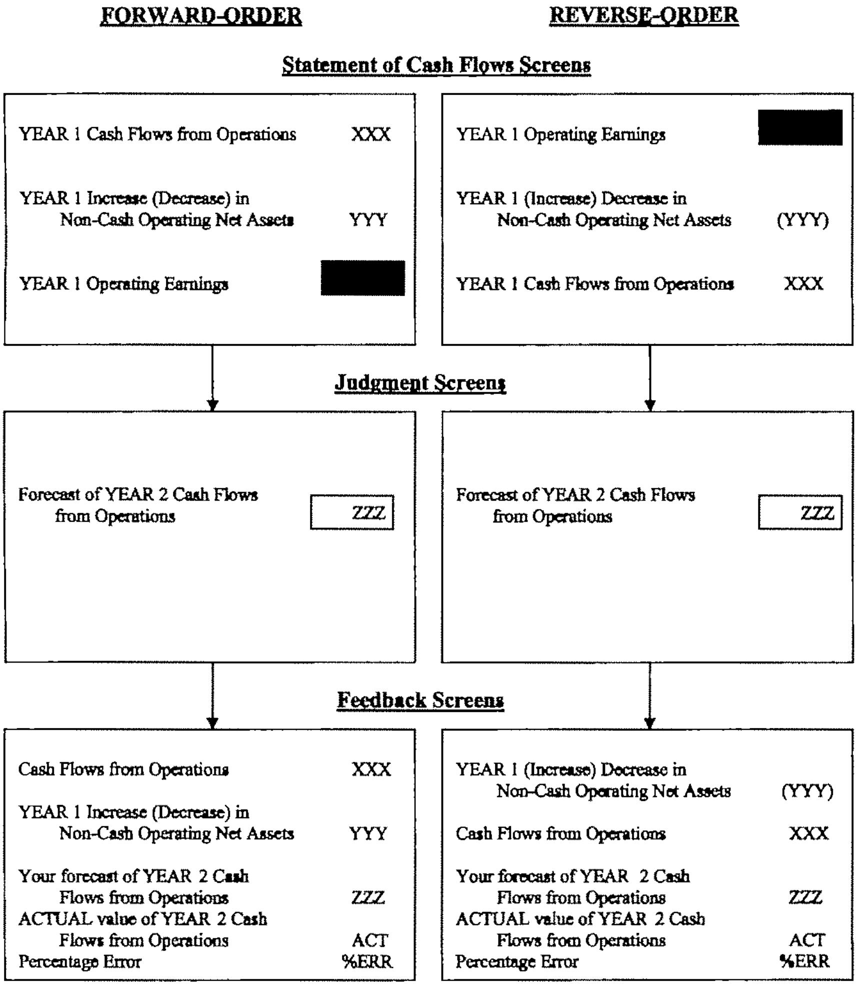
Participants completed the computerized experiment during a single monitored laboratory session. Computer administration allowed us to control the flow of information to participants, monitor the amount of time participants spent viewing individual screens, and to collect process-related data (e.g., the number of times participants viewed previous screens or the feedback pages). In addition, computer administration prevented participants from changing their forecasts after learning the actual outcomes. At the beginning of the experiment session, we provided participants with written and oral instructions describing how to access the computerized experiment, how to enter their responses during the session, how to receive compensation upon completion of the experiment, and the prohibited forms of assistance (e.g., computational aids, like Microsoft Excel®).

Participants completed a series of pre-experiment questions designed to assess their accounting knowledge, the perceived difficulty of the accounting knowledge questions, and their knowledge of the time-series relation between year-one *CFO* ($CFO_{t=1}$), year-one *CNOA* ($CNOA_{t=1}$), and year-two *CFO* ($CFO_{t=2}$). After finishing the pre-experimental-treatment questions, participants began the experimental task. The experimental task consisted of viewing $CFO_{t=1}$ and $CNOA_{t=1}$ information for 16 different companies and predicting $CFO_{t=2}$ for those companies. Figure 1 illustrates the primary computer screens for operationalizing the forward-order and reverse-order formats.

In the Reverse-Order (RO) condition, participants viewed three lines of information on the Statement of Cash Flows screen, in the following order: "YEAR 1 Operating Earnings" ($OE_{t=1}$), "YEAR 1 (Increase) Decrease in Non-Cash Operating Net Assets" ($CNOA_{t=1}$) and "YEAR 1 Cash Flows from Operations" ($CFO_{t=1}$). The actual amount of $OE_{t=1}$ was masked by a black box. When ready, participants proceeded to the Judgment screen on which they provided their estimate of $CFO_{t=2}$. After participants entered a forecast amount, they viewed a screen that included only their forecast of $CFO_{t=2}$ and the actual $CFO_{t=2}$ realization. When ready, participants proceeded to the Feedback screen, which presented cumulative, comprehensive summary information, including $CFO_{t=1}$, $CNOA_{t=1}$, actual $CFO_{t=2}$, the participants' forecast of $CFO_{t=2}$, and the percentage forecast error for each of their own previous forecasts.

Our second between-subjects condition, Forward-Order (FO), differed from RO in two ways. First, the Statement of Cash Flows screen included company data in the following order (i.e., opposite of the reverse-order): $CFO_{t=1}$, $CNOA_{t=1}$, and $OE_{t=1}$ (again masked). Second, the Feedback screen included the same cumulative, comprehensive summary information as the RO condition, except the feedback information was presented in the order of the Statement of Cash Flows screen for the FO condition.

FIGURE 1
Format of Financial Information, Judgment Elicitation, and Feedback Screens across Conditions



Statement of Cash Flows Screens

FORWARD-ORDER		REVERSE-ORDER	
YEAR 1 Cash Flows from Operations	XXX	YEAR 1 Operating Earnings	[redacted]
YEAR 1 Increase (Decrease) in Non-Cash Operating Net Assets	YYY	YEAR 1 (Increase) Decrease in Non-Cash Operating Net Assets	(YYY)
YEAR 1 Operating Earnings	[redacted]	YEAR 1 Cash Flows from Operations	XXX

Judgment Screens

FORWARD-ORDER		REVERSE-ORDER	
Forecast of YEAR 2 Cash Flows from Operations	ZZZ	Forecast of YEAR 2 Cash Flows from Operations	ZZZ

Feedback Screens

FORWARD-ORDER		REVERSE-ORDER	
Cash Flows from Operations	XXX	YEAR 1 (Increase) Decrease in Non-Cash Operating Net Assets	(YYY)
YEAR 1 Increase (Decrease) in Non-Cash Operating Net Assets	YYY	Cash Flows from Operations	XXX
Your forecast of YEAR 2 Cash Flows from Operations	ZZZ	Your forecast of YEAR 2 Cash Flows from Operations	ZZZ
ACTUAL value of YEAR 2 Cash Flows from Operations	ACT	ACTUAL value of YEAR 2 Cash Flows from Operations	ACT
Percentage Error	%ERR	Percentage Error	%ERR

Participants were randomly assigned to one of two format conditions. After completing the pre-experiment questions, participants provided forecasts of year-two cash flows from operations for 16 different companies. We counterbalanced the order of the companies (eight unique orders: four different rotated orders with reversals of those orders) to ensure that all 16 companies were equally represented across all 16 trials. For any given company, the information provided across the conditions was identical. However, the presentation of the information differed in a manner consistent with the "Statement of Cash Flows Screens" and "Feedback Screens" illustrated in the figure. After each judgment, participants were provided with comprehensive and cumulative feedback information for all of their judgments (e.g., immediately prior to their 16th forecast, participants could view the information on the "Feedback Screens" for all 15 of their proceeding forecasts. Upon completing forecasts for the 16 different companies, the participants provided responses to an identical set of post-experiment questions (e.g., demographic questions).
%ERR = (ACT-ZZZ)/ACT.

After completing their forecasts for each of the 16 companies, participants completed several post-experiment questions designed to elicit perceived task difficulty and judgment confidence. Participants were asked to assign weights to the values of $CFO_{t=1}$ and $CNOA_{t=1}$ in predicting $CFO_{t=2}$, based on their self-insight into the weights they assigned in the last set of predictions they made. Finally, participants were asked to supply answers to several demographic questions.

Upon completing the experiment, participants left the computer laboratory and were compensated based on the absolute value of their forecast errors. Compensation rates were determined based on average forecast errors of students who pre-tested the experiment. All participants were eligible to earn between \$6 and \$20, with actual payoffs spanning that range. The mean payoff was \$13.

Company Data Included in the Experiment Materials

Information for 500 companies was generated through a simulation based on Barth, Cram, and Nelson (2001). Specifically, $CFO_{t=2}$ was modeled as a linear function of $CFO_{t=1}$ and $CNOA_{t=1}$. Panel A of Table 2 provides the parameters of the generating function. We seeded a zero-mean, normally distributed error term into the simulation to add a small amount of noise to the subsequent realization of CFO (i.e., $CFO_{t=2}$).

We chose 16 firms from the model-generated observations. We intentionally selected companies to obtain a balanced design across all possible combinations of positive and negative operating cash flow and operating asset changes (+/+, +/−, −/+, −/−), crossed with randomly assigned positive and negative model errors. In Panel B of Table 2, we present the task information for the 16 firms we include in our experiment. Panel C of Table 2 presents descriptive statistics for the 16 selected firms. Although selection of sample firms was not random, parameters estimated from regressing sample values of $CFO_{t=2}$ on $CFO_{t=1}$ and $CNOA_{t=1}$ do not differ from theoretical model parameters.[5]

IV. RESULTS OF THE EXPERIMENT

Pre-Experiment Knowledge Questions

Prior to beginning the forecasting task, participants completed an accruals knowledge test, and assessed the difficulty of the test. Participants were required to successfully complete the knowledge test before they could proceed to the 16-company forecasting task. Table 1, Panel B indicates that almost all participants in both treatment groups correctly answered the required test questions on the first attempt. Participants rated these questions as relatively easy with a combined mean difficulty rating of 4.61 on a 15-point scale, increasing in perceived difficulty. Perceived difficulty of the tutorial task did not differ across groups ($Z = -0.73$ and $Z = -0.95$, both two-tailed p-values >0.10). Overall, the results reported in Panels A and B suggest that random assignment of participants across conditions successfully distributed knowledge and abilities across the two treatment groups.

Panel C of Table 1 presents participants' post-experiment self-assessments of forecast-task difficulty and forecasting confidence. Neither the participants' perceived difficulty of the forecast task ($Z = 0.55$, two-tailed p-value >0.10) nor their forecast-related confidence levels differed

---

[5] Across the two conditions, we presented the 16 firms in eight unique sequences. Four of the sequences were based on a four-firm rotation. Specifically, the firm randomly assigned as Firm 1 in Sequence 1, is Firm 5 in Sequence 2, Firm 9 in Sequence 3 and Firm 13 in Sequence 4. The remaining four sequences are an exact reversal of Sequences 1 through 4. Therefore, the firm randomly assigned as Firm 1 in Sequence 1 is Firm 16 in Sequence 5, Firm 12 in Sequence 6, Firm 8 in Sequence 7 and Firm 4 in Sequence 8. These eight unique sequences assures that every firm appears with equal frequency in Trials 1–4, 5–8, 9–12, and 13–16. This also results in equal representation of the positive and negative operating cash flow and operating asset changes (+/+, +/−, −/+, −/−) across the trials in each condition.

TABLE 3
Experiment Results
Forecast Errors and Dispersion of Forecast Judgments

Panel A: Forecast Error Median (Mean) [Standard Deviation]

	Reverse-Order			Forward-Order			Across Orders		
	First Half	Last Half	Overall	First Half	Last Half	Overall	First Half	Last Half	Overall
+CF / −ACC	0.20	0.21	0.20	0.19	0.14	0.14	0.20	0.15	0.18
	(0.29)	(0.45)	(0.37)	(0.33)	(0.23)	(0.28)	(0.31)	(0.34)	(0.32)
	[0.27]	[1.19]	[0.85]	[0.36]	[0.25]	[0.32]	[0.32]	[0.86]	[0.64]
−CF / +ACC	1.14	1.01	1.05	1.20	0.37	0.75	1.20	0.49	0.93
	(2.77)	(1.81)	(2.27)	(2.01)	(1.17)	(1.60)	(2.37)	(1.50)	(1.94)
	[5.09]	[2.83]	[4.08]	[2.98]	[1.99]	[2.58]	[4.12]	[2.47]	[3.42]
Across Mixed Sign	0.41	0.29	0.39	0.49	0.20	0.35	0.43	0.25	0.36
	(1.48)	(1.16)	(1.32)	(1.17)	(0.70)	(0.94)	(1.32)	(0.93)	(1.13)
	[3.72]	[2.30]	[3.09]	[2.28]	[1.49]	[1.95]	[3.07]	[1.95]	[2.59]
+CF / +ACC	0.21	0.29	0.24	0.21	0.17	0.18	0.21	0.22	0.21
	(0.34)	(0.36)	(0.35)	(0.30)	(0.26)	(0.28)	(0.32)	(0.31)	(0.31)
	[0.31]	[0.35]	[0.33]	[0.28]	[0.23]	[0.25]	[0.29]	[0.30]	[0.29]
−CF / −ACC	0.29	0.26	0.28	0.30	0.16	0.18	0.29	0.18	0.22
	(0.56)	(0.61)	(0.59)	(0.45)	(0.28)	(0.36)	(0.51)	(0.44)	(0.47)
	[0.69]	[0.69]	[0.69]	[0.48]	[0.36]	[0.43]	[0.59]	[0.57]	[0.58]
Across Same Sign	0.26	0.28	0.27	0.21	0.17	0.18	0.24	0.19	0.22
	(0.44)	(0.49)	(0.47)	(0.37)	(0.27)	(0.32)	(0.41)	(0.38)	(0.39)
	[0.54]	[0.57]	[0.55]	[0.40]	[0.30]	[0.35]	[0.47]	[0.46]	[0.47]

(continued on next page)

TABLE 3 (continued)

	Reverse-Order			Forward-Order			Across Orders		
	First Half	**Last Half**	**Overall**	**First Half**	**Last Half**	**Overall**	**First Half**	**Last Half**	**Overall**
Across Sign Groups	0.35 (0.96) [2.70]	0.29 (0.82) [1.70]	0.30 (0.89) [2.26]	0.37 (0.79) [1.71]	0.17 (0.47) [1.07]	0.22 (0.63) [1.43]	0.36 (0.87) [2.26]	0.22 (0.65) [1.43]	0.27 (0.76) [1.89]

Panel B: Repeated Measures Analysis of Variance on Rank Transformed Forecast Errors

Factors	df	F-value	$Pr > F^a$
Method	1	11.63	<0.001
MIXED	1	25.26	<0.001
Half	1	12.70	<0.001
NEG_CF	1	80.05	<0.001
Method × *MIXED*	1	0.38	0.535
Method × Half	1	6.57	0.011
Method × *NEG_CF*	1	0.89	0.346
MIXED × Half	1	2.76	0.097
MIXED × *NEG_CF*	1	57.74	<0.001
Half × *NEG_CF*	1	3.14	0.077
Method × *MIXED* × Half	1	0.09	0.771

(continued on next page)

TABLE 3 (continued)

Factors	df	F-value	$Pr > F^a$
Method × *MIXED* × *NEG_CF*	1	0.01	0.923
MIXED × Half × *NEG_CF*	1	0.13	0.719
Method × *MIXED* × Half × *NEG_CF*	2	0.50	0.605
Error	784		

Panel C: Repeated Measures Analysis of Variance on Rank Transformed Variability Measure[b]

Factors	df	F-value	$Pr > F^a$
Method	1	44.17	<0.001
MIXED	1	20.75	<0.001
Half	1	6.01	0.015
NEG_CF	1	169.13	<0.001
Method × *MIXED*	1	2.75	0.098
Method × Half	1	24.37	<0.001
Method × *NEG_CF*	1	0.74	0.390
MIXED × Half	1	0.05	0.822
MIXED × *NEG_CF*	1	71.50	<0.001
Half × *NEG_CF*	1	10.73	0.001
Method × *MIXED* × Half	1	0.08	0.782
Method × *MIXED* × *NEG_CF*	1	3.05	0.081
MIXED × Half × *NEG_CF*	1	0.52	0.472
Method × *MIXED* × Half × *NEG_CF*	2	0.42	0.654
Error	784		

(continued on next page)

TABLE 3 (continued)

---

[a] Reported p-values represent two-tailed tests of significance.

[b] Rank transformed variability measure is generalized from the nonparametric test for differences in dispersion suggested by Fligner and Killeen (1976) as modified by Conover et al. (1981). The dependent measure is computed by transforming the absolute value of the difference between each observation and its corresponding cell median. The transformation used is $\Phi^{-1}(0.5 + i / 2(N + 1))$ where Φ^{-1} represents the inverse standard normal distribution function, i is the ranked absolute value, and N is the combined sample size of all experimental cells.

Variable Definitions:

Forecast Error = the absolute percentage error subjects response deviated from $CFO_{t=2}$ calculated by taking the absolute value of the difference between actual $CFO_{t=2}$ and subject's estimate of $CFO_{t=2}$ divided by the model estimate $CFO_{t=2}$;

MIXED/SAME = dichotomous variable equal to 1 (0) if the sign of $CFO_{t=1}$ and the sign of $CNOA_{t=1}$ were (were not) the same;

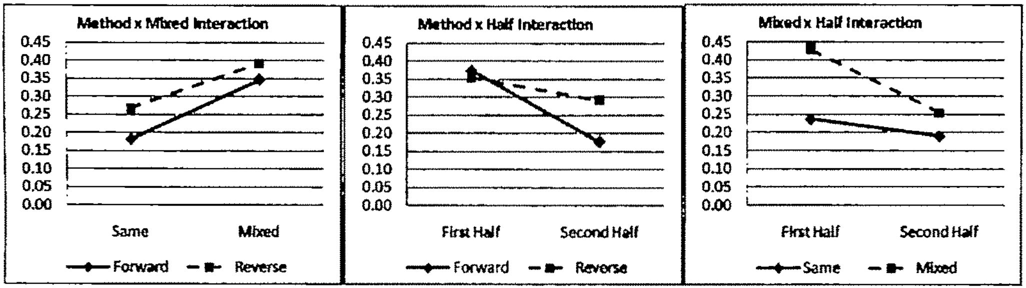
First/Last Half = dichotomous variable equal to 1 (0) if the subject estimated $CFO_{t=2}$ in the first (last) eight trials of the experiment;

Method = dichotomous variable equal to 1 (0) if the presentation format was RO (FO); and

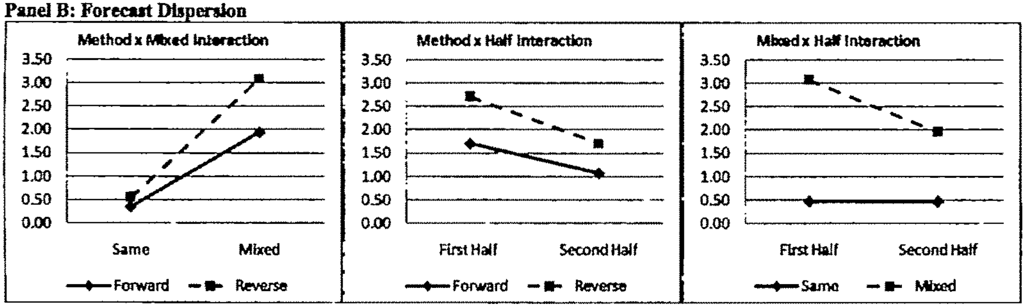
NEG_CF = dichotomous variable equal to 1 (0) if the $CFO_{t=1}$ is less (greater) than 0.

FIGURE 2
Format of Financial Information, Judgment Elicitation, and Feedback Screens across Conditions

Panel A: Median Forecast Errors



Panel B: Forecast Dispersion



The interactions graphed correspond to the interaction effects tested in Table 3, Panel B and Panel C.

× Half" interactions. The significant main effects for "Half" in Table 3, Panels B and C indicate that median forecast errors (0.36 compared to 0.22; F = 12.70, two-tailed p-value <0.001) and forecast dispersion (2.59 compared to 0.47; F = 6.01, two-tailed p-value = 0.015), respectively, are greater in the first eight trials than in the last eight trials. Consistent with differential learning evidenced by participants across the two methods, forward-order showed a statistically significant decline in median forecast errors (0.37 versus 0.17; Z = 3.48, two-tailed p-value <0.001, untabulated) over the last eight trials compared to the first eight, while the forecast error remained statistically flat in the reverse-order condition (0.35 versus 0.29; Z = 0.37, two-tailed p-value >0.10, untabulated). In comparison, forecast dispersion experienced significant declines in forward-order (1.71 versus 1.07; F = 2.54, two-tailed p-value <0.001, untabulated) and reverse-order (2.70 versus 1.70; F = 2.53, two-tailed p-value <0.001, untabulated), with reverse-order actually experiencing a statistically larger decline in dispersion. This higher rate of improvement in the reverse-order is mainly the result of reverse-order having a relatively high level of dispersion in the first eight trials. Indeed, even after experiencing a higher rate of improvement, the level of dispersion for the last eight trials of reverse-order is statistically equal to the level of dispersion for the first eight trials of forward-order (1.71 versus 1.70; F = 1.01, two-tailed p-value >0.10, untabulated). Table 3, Panels B and C also presents the results of tests that compare participants' accuracy and dispersion across same-versus-mixed signs of $CNOA_{t=1}$ and $CFO_{t=1}$. Hypotheses 2a and 2b predict that forecast error and dispersion increase with task complexity. In our cash flow forecasting context, we propose that task complexity increases when data inputs have conflicting signs. Consistent with H2a, the significant main effect for "Mixed" in Table 3, Panel B (see non-shaded boxes in Table 3, Panel A; 0.36 compared to 0.22; F = 25.26, one-tailed p-value < 0.001) indicates that forecast errors are higher for companies with mixed-sign inputs compared to companies with same-sign inputs. Consistent with H2b, the significant main effect for "Mixed" indicates that dispersion is higher for companies with mixed-sign inputs (see non-shaded boxes in Table 3, Panel A; standard deviation of 2.59 compared to 0.47; F = 20.75, one-tailed p-value < 0.001). These results are reported after controlling for negative CFO_{t-1}. Consistent with our expectation, participants appeared to make significantly greater forecast errors (NEG_CF in Table 3, Panel B; F = 80.05; one-tailed p-value < 0.001) and experience significantly greater forecast dispersion (NEG_CF in Table 3, Panel C; F = 169.13; one-tailed p-value < 0.001) when the firm reported negative cash flows in the learning data.[10]

The analyses reported in Panels B and C of Table 3 also reveal significant "Mixed × NEG_CF" interaction terms for participants' forecast error (F = 57.74, two-tailed p-value < 0.001) and forecast dispersion (F = 71.50, two-tailed p-value < 0.001), respectively. These statistics suggest that interpretation of the predicted main effects in the mixed- versus same-sign hypotheses tests are qualified because the magnitude of the effect is different within either the same-sign or the mixed-sign pairs. Closer inspection of the disaggregated mixed-sign and same-sign forecast errors and forecast dispersion reported in Table 3, Panel A reveals that the "$-CF/+ACC$" cell had higher levels of forecast error (median = 0.93) and forecast dispersion (standard deviation = 3.42) than the three other sign combinations. Further analysis reveals, between the positive $CFO_{t=1}$ conditions, forecast error is marginally different between the same and mixed-sign conditions (0.18 versus 0.21, Z = −1.64, two-tailed p-value < 0.10, untabulated); however, forecast dispersion is statistically higher in the mixed-sign condition (0.64 versus 0.29, F = 4.70, two-tailed p-value < 0.001, untabulated). Between the negative $CFO_{t=1}$ conditions, forecast error (0.93 versus 0.22, Z = 7.24, two-tailed p-value < 0.001 untabulated) and forecast dispersion (3.42 versus 0.58, F = 34.58, two-tailed p-value < 0.001, untabulated) are higher in the mixed-sign conditions. Taken together, these results suggest that our experimental findings related to forecast error are primarily driven by the unusual combination of $-CF/+ACC$, but that our findings related to forecast dispersion are robust across either sign of $CFO_{t=1}$. In designing this study, we were primarily interested in the mixed- versus same-sign comparisons, and introduced the four different sign combinations to balance the research design. We did not design the experiment to specifically investigate the forecast effects of negative *CFO* and we did not collect debriefing data on participants' perceptions of negative *CFO* firms. Thus, the negative *CFO* effect could be caused by naïve beliefs about negative *CFO* firms or by computational complexity caused by reported negative *CFO*.

Implicit Model Weights

To further explore the data, we compare the model weights implicitly evidenced by the 16 trials of forecasts provided by participants. As reported in Table 4, we extracted implicit subject model weights for $CFO_{t=1}$ and $CNOA_{t=1}$ by regressing subject forecasts of $CFO_{t=2}$ on current levels of $CFO_{t=1}$ and $CNOA_{t=1}$. The mean (median) weight placed on $CFO_{t=1}$ by the forward-order participants is 0.90 (0.91) compared to 0.96 (0.91) for the reverse-order condition. Although the means marginally differ, the identical medians confirm that the difference is not statistically significant. Therefore, it appears that participants in both conditions underweight $\mathrm{CFO}_{t=1}$ by the same amount relative to the theoretical model weight. The insignificant difference in subject

---

[10] Our inferences are the same if we omit NEG_CF_{t-1} from the analysis.

TABLE 4
Extracted Model Weights by Condition

	Forward Order	Reverse Order	Comparison of Forward-Order to Reverse-Order
Subject Weights on CFO_{t-1}			
Mean	0.90#	0.96	(Wilcoxon Z-stat = 0.12)
Median	0.91##	0.91##	(Median Z-stat = −0.28)
Standard Deviation	0.25	0.45	(Folded F-value = 3.38)***
Minimum	0.26	0.13	
Maximum	1.29	2.88	
Mean deviation from theoretical value	−0.10	−0.04	(Wilcoxon Z-stat = 0.12)
Subject Weights on $CNOA_{t-1}$			
Mean	0.50	0.41#	(Wilcoxon Z-stat = 2.17)**
Median	0.50	0.34###	(Median Z-stat = 1.96)**
Standard Deviation	0.23	0.44	(Folded F-value = 3.70)***
Minimum	0.05	−0.37	
Maximum	1.24	2.06	
Mean deviation from theoretical value	−0.05	−0.14	(Wilcoxon Z-stat = 2.17)**

*,**,*** Differences across conditions are significant (two-tailed), p-value ≤ 0.10, 0.05, and 0.01 levels of significance, respectively.

#,##,### Amount varies from its theoretical value at (two-tailed) p-value ≤ 0.10, 0.05, and 0.01 levels of significance, respectively.

Subject weight parameters are obtained by estimating the following model for each subject over 16 forecast trials:

$$CFO_{t,s} = \beta_s CFO_{t-1} + \beta_s CNOA_{t-1} + \varepsilon_s.$$

Mean deviations from the theoretical parameter values are calculated using the same model weights implicit in the generated data (1.0 for CFO_{t-1} and 0.55 for $CNOA_{t-1}$).

Nonparametric comparisons were made using the Wilcoxon-Mann-Whitney test and Median tests where appropriate.

model weights on $CFO_{t=1}$ is not surprising given that $CFO_{t=1}$ was similarly displayed in both conditions. Interesting differences across conditions are revealed by the subject weights on $CNOA_{t=1}$. Specifically, our evidence shows that participants robustly underweight $CNOA_{t=1}$ in the reverse-order condition (mean weight of 0.41 compared to the theoretical value of 0.55), while participants in the forward-order condition assign an average weight of 0.50 to $CNOA_{t=1}$, which does not statistically differ from the theoretical value but does significantly differ from the reverse-order condition ($Z = 2.17$, p-value < 0.05). This pattern of results is even more pronounced for median implied $CNOA_{t=1}$ weights.

This pattern of results is consistent with reverse-order participants failing to fully adjust for the sign reversal inherent in the reverse-order presentation.[11] Cross-subject dispersion is also much higher in the reverse-order condition. Implied model weights for $CFO_{t=1}$ in the reverse-order condition range from 0.13 to 2.88 (standard deviation of 0.45) compared to the implied $CFO_{t=1}$ model weights in the forward-order condition, which range from 0.26 to 1.29 (standard deviation of 0.25). The relatively high dispersion across participants in the reverse-order condition is also apparent in participants' weights on $CNOA_{t=1}$ which range from −0.37 to 2.06 (standard deviation of 0.44). In contrast, subject weights on $CNOA_{t=1}$ in the forward-order condition range from 0.05 to 1.24 (standard deviation of 0.23). These results provide additional support for hypothesis H1b that dispersion is higher among participants in the reverse-order condition.

---

[11] Recall that increases (decreases) in operating assets are displayed as negative (positive) numbers in the reconciliation of income to *CFO*. Subjects evaluating the reverse-order format must translate a number subtracted in arriving at *CFO* in the current period into an increase in future *CFO*.

Discussion of Design Choices in Experiment

We incorporated a highly simplified statement of cash flows into our experiment because we wanted to conduct the cleanest possible test of direction-related cash-flow-statement format effects. This parsimonious design may lead to two concerns about the interpretation of our study: first, that our results may not generalize to a setting where an operating-earnings metric is also presented, and second, that we caused participants to engage in an additional, effortful, and irrelevant mental process to compute earnings. We provide discussion of the technical aspects of these issues in the space that follows. In the "Summary and Conclusion" section of this paper, we discuss these issues in the context of generalizability of our results and implications for potential future research.

As illustrated in Figure 1, experiment participants viewed initial statement of cash flows screens that included an opaque box where each operating-earnings (*OE*) total appeared in a complete statement of cash flows. This design provides only the essential period $t = 1$ diagnostic information for the prediction of $CFO_{t=2}$ (i.e., $OE_{t=1}$ is a redundant, linear combination of $CFO_{t=1}$ and $CNOA_{t=1}$), while also manipulating the directional format of that information. Because we hypothesize that the directional orientation of the cash flow statement leads to differential processing complexity, we were concerned that participants facing higher processing complexity would be more likely to fixate on $OE_{t=1}$ as an easy-to-process short-cut cue for forecasting $CFO_{t=2}$. Further, this strategy would result in larger forecast errors because it fails to differentially weight $CNOA_{t=1}$ and $CFO_{t=1}$. Thus, if $CFO_{t=1}$, $CNOA_{t=1}$, and $OE_{t=1}$ are simultaneously presented, we cannot unambiguously attribute differential forecast error or forecast dispersion to the direction of information in the cash flow statement instead of a greater propensity to fixate on earnings when additional cognitive effort is required. Our research design potentially trades off generalizability to eliminate this alternative explanation.

The second concern is that the presence of the opaque "operating earnings" black box illustrated in Figure 1 might have caused an earnings-fixated subset of participants to attempt to solve for the amount implied by the box (i.e., $OE_{t=1}$), instead of directly using the two amounts in the $CFO_{t=2}$ prediction task. This unobservable (and unnecessary) mental process is likely not problematic if it is distributed evenly over the two format conditions (i.e., it would uniformly increase error in the data); however, it is a much greater concern if this extra mental computation disproportionately occurs in either of the two formats. Three items in our study suggest that this possibility is unlikely. First, the introductory training task was written to have all participants maximize accuracy. In particular, they were instructed that their compensation depended on forecast accuracy and that $CFO_{t=2}$ is a function of $CFO_{t=1}$ and $CNOA_{t=1}$, (i.e., $OE_{t=1}$ was not included on the training screen). Second, a common proxy for mental-processing attention and effort is the amount of elapsed time in completing a given task. We collected the amount of elapsed time that each subject viewed each screen and note that the average time spent on the "Statement of Cash Flows Screens" (i.e., see top screens in Figure 1) was not different between the forward- and reverse-order conditions (forward mean = 23.1 seconds versus reverse mean = 21.4 seconds, t = 0.61, two-tailed p-value >0.10, untabulated). Third, in terms of the true model weights expressed in Table 2, Panel A, an earnings-fixated approach to forecasting $CFO_{t=2}$ would give the appearance that participants applied $\beta_1 = \beta_2$ in their forecast judgments, assuming a random-walk forecast-judgment rule. However, the extracted model weights presented in Table 4 are inconsistent with this conjecture because neither group significantly overweights $CNOA_{t=1}$. Overall, we believe that the existence of the black box did not disproportionately affect either directional format-related treatment over the other.

V. QUASI-EXPERIMENT WITH ANALYSTS' CASH FLOW FORECASTS

In this section, we provide evidence on the effects of informational complexity in the context of passively observed, published cash flow forecasts produced by financial analysts and disseminated via two popular data providers: I/B/E/S and the Value Line Investment Survey. Given the relative strengths and weaknesses of each of these sources of published analyst cash-flow-forecast data (discussed in greater detail in each of the following subsections), we conduct and report analyses with each data set.

Quasi-Experimental Design: I/B/E/S Data

To obtain our I/B/E/S sample, we first identify U.S. firms with one-year-ahead cash flow forecasts in the I/B/E/S detail history for the period 1994 through 2006 and collect predicted values of cash flow per share.[12] From the I/B/E/S detail file, we identify the first forecast for the next fiscal year made by each analyst subsequent to release of the prior period's financial statements and more than three months prior to the next fiscal year-end. For this purpose, we assume financial statements are released within three months of each firm's fiscal year-end.[13]

We collect realized (actual) cash flow per share from I/B/E/S to ensure that predicted and realized cash flows are reported on a consistent measurement basis. Price data are obtained from CRSP, and all other financial statement data are obtained from Compustat. We exclude from our analysis firms in the banking and insurance industries because measures of operating accruals for these firms are not comparable to those in other industries. We identify 1,431 unique firms for which price data, at least one cash flow forecast, and a corresponding actual value are reported. Merging these observations with Compustat reduces the number of unique firms to 1,135. Missing data and data screens further reduce the sample, resulting in a final count of 897 unique firms with 2,188 observations over the time-series (mean = 2.4 observations per firm).[14]

In contrast to the research design of our experiment, we are unable to directly control by assignment factors in our quasi-experiment that (1) are likely to influence forecast accuracy and (2) may also be correlated with our proxy for informational complexity. Specifically, in our quasi-experiment we cannot impose a single cash-flow-generating process across conditions, companies, and time. Thus, firms exhibiting $MIXED_{t-1}$ accruals and cash flows may differ from those with consistently signed accruals and cash flows in the average variability of accruals and cash flows, relative magnitude of accruals, length of the operating cycle, size, industry, growth, or other dimensions.

Constructing a comprehensively matched control sample along all of these dimensions is not possible with our sample of 897 firms. Therefore, we are left with two viable research design choices. First, we can augment a regression with proxies that control for differences in firms' underlying cash-flow-generating processes. Second, we can use each firm as its matched control and compare forecast errors across $MIXED_{t-1}$ and $SAME_{t-1}$ years. Because each of these approaches has strengths and weaknesses, we implement both.

---

[12] Cash flow forecasts prior to 1994 are eliminated due to their low frequency.

[13] For example, for a firm with a year ending December 31, 1993, we collect the first forecast of fiscal 1994 cash flows by each analyst made subsequent to March 31, 1994, but prior to October 1, 1994. Results are robust to assuming that financial statements are released on the earnings release date provided by I/B/E/S.

[14] Consistent with Barth, Cram, and Nelson (2001), we trim all values at the 1st and 99th percentiles. As well, we eliminate all firms with special items. Missing data, primarily cash flows, accounts for the remaining sample contraction.

Analysis Based on Cross-Sectional Regression with Comprehensive Set of Control Variables

We begin with an augmented regression of $ERROR_t$ on $MIXED_{t-1}$ in which we attempt to identify significant factors that may be correlated with informational complexity:

$$\begin{aligned} ERROR_t = {} & \beta_0 + \beta_1 MIXED_{t-1} + \beta_2 NEG\_CFO_{t-1} + \beta_3 OP\_CYCLE_{t-1} + \beta_4 \sigma CFO_{t-5,t} \\ & + \beta_5 \sigma CNOA_{t-5,t} + \beta_6 RANK\_|CNOA_{t-1}| + \beta_7 SIZE_{t-1} + \beta_8 PROFITABILITY_{t-1} \\ & + \beta_9 GROWTH_{t-1} + \sum_{j=1}^{12} \beta_{10,j} INDUSTRY_{j,t-1} + \varepsilon_t. \end{aligned} \tag{1}$$

$ERROR_t$ is the absolute value of the difference between the actual cash flow per share reported by I/B/E/S for a given year and the mean forecasted cash flow per share predicted by I/B/E/S analysts.[15] $ERROR_t$ is deflated by the average price over the forecast period. We use the absolute value of $ERROR_t$ because our primary interest is in average accuracy (the relative magnitude of forecast errors), rather than average optimism or pessimism (bias). We include $MIXED_{t-1}$ as an explanatory variable to proxy for informational complexity. $MIXED_{t-1}$ is set to 1 when CFO_{t-1} and changes in net operating assets ($CNOA_{t-1}$) are of different signs (positive CFO_{t-1} and negative $CNOA_{t-1}$, or negative CFO and positive $CNOA_{t-1}$). For our tests, $CNOA_{t-1}$ is measured as net working-capital accruals. Net working-capital accruals is the sum of increases in accounts receivable (Data302) and inventories (Data303) minus the sum of increases in accounts payable (Data304) and accrued taxes (Data305).[16] We predict a positive coefficient on $MIXED_{t-1}$ because forecast error is expected to increase with informational complexity. Because firms with negative operating cash flows may increase informational complexity beyond $MIXED_{t-1}$, we include a dummy variable for negative cash flows (NEG_CFO_{t-1}) to capture the marginal effect of negative cash flows on forecast accuracy. We expect a positive coefficient estimate for NEG_CFO_{t-1}.

In our experiment, we hold the cash flow operating cycle constant so that each firm will realize the same proportion of year-one accruals in year 2. Across archival firms, Barth, Cram, and Nelson (2001), show that the predictive ability of accruals for future cash flows depends on each firm's cash operating cycle. If firms exhibiting $MIXED_{t-1}$ accruals and cash flows tend to have longer operating cycles, then differences in cash operating cycles could account for any higher forecast errors observed for $MIXED_{t-1}$ firm years. To control for this, we calculate an operating cycle proxy (OP_CYCLE) equal to δ in Dechow et al. (1998) and Barth, Cram, and Nelson (2001). Specifically, $OP\_CYCLE = [\alpha + (1-\pi)\gamma - \beta(1-\pi)]$, where $\alpha = (AR_t + AR_{t-1}) / 2\ S_t$; $\beta = (AP_t + AP_{t-1}) / 2\ S_t\ (1-\pi)$; $\pi = E_t / S_t$; $\gamma = g_1 / (1-\pi)$, where g_1 is the estimated coefficient on S_t in a regression of INV_t on S_t and ΔS_t. Financial statement variables are obtained from Compustat, where AR is accounts receivable (Data2); S is sales (Data12); AP is accounts payable (Data70 + Data153); E is income before extraordinary items (Data123); and INV is inventory (Data3). OP_CYCLE_{t-1} is expressed as a fraction of a year. We expect a positive coefficient on

---

[15] Results are robust to using the median forecast instead of the mean. We use mean forecasts to maximize the sample size for within-firm tests.

[16] We exclude increases in other assets and liabilities (Data307) because this line item frequently includes changes in *long-term* assets and liabilities (e.g., those related to pensions).

OP_CYCLE_{t-1} because longer operating cycles mean that current period accruals are less likely to be realized in the next period and should have less predictability for one-year-ahead cash flows.

In designing the materials for our experiment, we draw from the same distributions the cash flow and accrual observations for all firms. Because the underlying distributions for accruals and cash flows likely differ across firms in our quasi-experiment, we include controls for CFO_{t-1} variability, $CNOA_{t-1}$ variability, and the frequency of extreme values in our archival regression. We measure CFO_{t-1} variability (i.e., σCFO_{t-1}) and $CNOA_{t-1}$ variability (i.e., $\sigma CNOA_{t-1}$) as the standard deviation of each over the five-year period ending with the forecast date. We predict positive coefficients on σCFO_{t-1} and $\sigma CNOA_{t-1}$ because greater variability is associated with lower predictability.

These variability measures should capture some of the cross-sectional differences in the propensity of firms to experience relatively extreme observations of accruals and cash flows. However, if extreme observations are more likely to occur in periods when accruals and cash flows are $MIXED_{t-1}$, then extreme observations could still account for any lower accuracy observed in the $MIXED_{t-1}$ group. Therefore, we include $RANK\_|CNOA_{t-1}|$ to explicitly control for the effects of extreme observations on forecast accuracy.[17] If analysts fail to fully consider mean-reverting tendencies of extreme performance realizations, then the absolute value of forecast errors should be higher following such realizations (Sloan 1996; Bradshaw et al. 2001); therefore, we expect a positive coefficient on $RANK\_|CNOA_{t-1}|$. To construct this variable, we rank the absolute value of $CNOA_{t-1}$ by year, within the population of Compustat firms. This process assigns higher ranks to those observations falling within the extreme positive or negative portions of the cross-sectional distribution for the year.

We are also unable to directly control through randomization or assignment factors associated with analysts that may influence forecast accuracy. For example, more competent analysts may choose to follow firms with greater information complexity because of potential rewards associated with the identification of mispricing (Barth, Kasznik, and McNichols 2001). If more competent analysts are more accurate, this would work against finding lower accuracy for $MIXED_{t-1}$. Alternatively, analyst coverage may be greater for firms with richer, less complex information environments (Healy et al. 1999). Greater coverage should result in consensus forecasts with less idiosyncratic error. To the extent that less idiosyncratic error results in smaller forecast errors, greater analyst coverage could result in lower errors for firm with less informational complexity. We include the log of assets, $SIZE_{t-1}$, to control for these potential structural differences in the information environments.[18] Because $SIZE_{t-1}$ can operate to either increase or decrease forecast accuracy, we do not predict a sign for this variable.

$PROFITABILITY_{t-1}$ and $GROWTH_{t-1}$ may also be correlated with $MIXED_{t-1}$. Specifically, negative net working capital accruals may reflect a contraction due to lower product demand. If less profitable and slower-growing firms are more difficult to forecast, then forecast errors may be negatively associated with profitability and growth. Alternatively, firms that consistently report high levels of profitability may obscure the underlying data-generating process for cash flows through earnings management, leading to greater forecast errors. To control for these potential differences across firms, we include long-run average $PROFITABILITY_{t-1}$ and $GROWTH_{t-1}$ as control variables. Following Dechow et al. (1998), we compute $PROFITABILITY_{t-1}$ as income before extraordinary items (Data123) divided by sales (Data12). We compute $GROWTH_{t-1}$ as the percentage change in sales ($[SALES_t - SALES_{t-1}] / SALES_{t-1}$). We average $PROFITABILITY_{t-1}$ and $GROWTH_{t-1}$ over the five-year period ending with the forecast date. Because $PROFITABILITY_{t-1}$ and $GROWTH_{t-1}$ may operate to increase or decrease forecast accuracy, we do not predict signs for these variables. Finally, because Barth, Cram, and Nelson (2001) suggest that the time-series properties of cash flows are influenced by industry, we include twelve industry control variables consistent with their classification.

---

[17] We also include year effects and firm effects to control for potential clustering of observations within periods or by firm.

[18] Because of the short time-series of available forecasts and discontinuities in coverage, we do not have sufficient data to compute individual analyst accuracy for the majority of analysts in our sample. We do find that results are robust to including the number of analysts following each company as a control variable. This variable is highly correlated with $SIZE_{t-1}$. We prefer $SIZE_{t-1}$ as a control variable because it exhibits more variation than analyst following. Analyst following exhibits little cross-sectional variation within each quartile of sample firms by size.

Analysis Based on Each Firm as its Own Control

If our augmented regression fails to include potential unidentified firm attributes that are correlated with $MIXED_{t-1}$, then we may incorrectly attribute observed differences to $MIXED_{t-1}$ rather than to the unidentified attributes. One way to mitigate this concern is to compare the magnitude of the forecast errors for each firm across $MIXED_{t-1}$ and consistent years. For example, if we represent our research design as Equation (2), where "identified firm attributes" represent the control variables identified in Equation (1), and "unidentified firm attributes" represent potential correlated omitted variables, then we can difference Equation (2) across $MIXED_{t-1}$ and $SAME_{t-1}$ years to arrive at Equation (3).

$$\begin{aligned} ERROR_t = f(&MIXED/SAME + IDENTIFIED\_FIRM\_ATTRIBUTES \\ &+ UNIDENTIFED\_FIRM\_ATTRIBUTES). \end{aligned} \tag{2}$$

$$\begin{aligned} ERROR\_MIXED - ERROR\_SAME = f(&\Delta IDENTIFIED\_FIRM\_ATTRIBUTES \\ &+ \Delta UNIDENTIFED\_FIRM\_ATTRIBUTES). \end{aligned} \tag{3}$$

In Equation (3), Δ represents change. To the extent that identified and unidentified firm attributes remain constant across $MIXED_{t-1}$ and $SAME_{t-1}$ firm-years, these changes will be zero and have no influence on the measured difference.[19] Therefore, we measure the effect of $MIXED_{t-1}$ by subtracting the average forecast error for all $SAME_{t-1}$ firm years from the average forecast error for all $MIXED_{t-1}$ firm years.

We point out several caveats to this approach. First, this approach does not mitigate the effect of unidentified firm attributes that may be correlated with $MIXED_{t-1}$ and may vary through time. Second, a limitation of our archival sample is that many of the archival firms are missing cash flow forecasts for one or more years across the 12-year measurement interval.[20] Because of this, many firms have insufficiently long time-series to exhibit both $MIXED_{t-1}$ and consistent characteristics over the measurement interval. Thus, this analysis significantly reduces the sample size and potentially introduces survivorship bias.

Results of the Quasi-Experiment: I/B/E/S Data

Results of Cross-Sectional Regression with Comprehensive Set of Control Variables

Panel A of Table 5 presents descriptive statistics for the sample of I/B/E/S firms used in the archival analysis. Means, standard deviations, medians, and quartiles are presented in columns two through six and means by mixed/same sign groups are presented in the last two columns.

---

[19] Although we cannot test this assumption for unidentified firm attributes, an untabulated analysis of identified firm attributes reveals no significant differences in OP_CYCLE_{t-1}, σCFO_{t-1}, $\sigma CNOA_{t-1}$, $RANK\_|CNOA_{t-1}|$, $SIZE_{t-1}$, long-run $PROFITABILITY_{t-1}$, long-run $GROWTH_{t-1}$ or $INDUSTRY_{t-1}$ across $MIXED_{t-1}$ and $SAME_{t-1}$ years for our sample firms.

[20] The mean break between observations is 1.47 years. The minimum (maximum) number of observations per firm is 1 (11). However, only 32 firms have six or more observations over the 12-year time-series. The significant discontinuities in coverage are consistent with the findings of DeFond and Hung (2003).

TABLE 5
I/B/E/S Sample Descriptive Statistics

Panel A: Distributional Statistics for Regression Variables (n = 2 , 189)

	All Observations					Means by Group	
Variable	**Mean**	**Std. Dev.**	**Q1**	**Median**	**Q3**	**Mixed Sign**	**Same Sign**
$ERROR_t$	0.036	0.078	0.007	0.017	0.036	0.044	0.031***
$MIXED_{t-1}$	0.339	0.474					
NEG_CFO_{t-1}	0.033	0.178	0.000	0.000	0.000	0.047	0.026**
$OP\_CYCLE_{t-5 \text{ to } t}$	0.191	0.140	0.095	0.160	0.251	0.207	0.182***
$\sigma CFO_{t-5 \text{ to } t}$	0.080	0.118	0.030	0.050	0.082	0.081	0.079
$\sigma CNOA_{t-5 \text{ to } t}$	0.068	0.125	0.019	0.038	0.072	0.072	0.066
$RANK\_\lvert CNOA_{t-1}\rvert$	3.400	2.436	1.000	3.000	5.000	3.406	3.397
$SIZE_{t-1}$	8.213	1.554	7.160	8.203	9.364	8.139	8.250
$PROFITABILITY_{t-5 \text{ to } t}$	0.088	0.056	0.048	0.075	0.114	0.084	0.091***
GROWTH_{t-1}	0.131	0.280	0.009	0.110	0.180	0.057	0.169***
CFO_{t-1}	0.118	0.112	0.053	0.093	0.155	0.129	0.112***
$CNOA_{t-1}$	0.011	0.091	−0.006	0.007	0.030	−0.039	0.037***
$INDUSTRY_{t-1}$							
Agriculture	0.002					0.001	0.003
Food	0.047					0.044	0.048
Textiles	0.068					0.093	0.055***
Chemicals	0.058					0.059	0.057
Pharmaceuticals	0.043					0.023	0.053***
Mining	0.164					0.141	0.175**
Other Extractive	0.142					0.118	0.154**

(continued on next page)

TABLE 5 (continued)

Variable	All Observations Mean	Std. Dev.	Q1	Median	Q3	Means by Group Mixed Sign	Same Sign
Durable Manufacturing	0.279					0.343	0.246***
Computers	0.092					0.106	0.085
Transportation	0.057					0.044	0.069***
Utilities	0.059					0.065	0.056
Retail	0.122					0.094	0.137***
Services	0.064					0.059	0.066
Other	0.005					0.007	0.004
n	2,188 (100.00%)					1,446 (66.10%)	742 (33.90%)

Panel B: Pearson (above the diagonal) and Spearman (below the diagonal) Correlations (n = 2,188)

	ERROR	*MIXED*	*NEG_CFO*	*OP_CYCLE*	σ*CFO*	σ*CNOA*	*RANK_|CNOA|*	*SIZE*	*PROFITABILITY*	*GROWTH*
$ERROR_t$		**0.078**	**0.061**	0.030	**0.259**	**0.261**	**0.177**	**−0.089**	**−0.088**	**−0.065**
MIXED	**0.061**		**0.057**	**0.084**	0.010	0.023	0.001	−0.034	**−0.064**	**−0.189**
NEG_CFO	**0.073**	**0.057**		**0.108**	**0.096**	**0.103**	**0.118**	**−0.111**	−0.008	−0.025
OP_CYCLE	**−0.077**	**0.097**	**0.105**		−0.029	0.025	**0.049**	−0.012	−0.041	**−0.097**
σ*CFO*	**0.350**	**0.067**	**0.090**	**−0.150**		**0.781**	**0.220**	**−0.119**	**−0.132**	0.016
σ*CNOA*	**0.275**	**0.091**	**0.134**	**0.045**	**0.693**		**0.317**	**−0.145**	**−0.218**	−0.011
RANK_|CNOA|	**0.200**	−0.002	**0.106**	0.025	**0.377**	**0.599**		**−0.140**	**−0.304**	**0.051**

(continued on next page)

TABLE 5 (continued)

	ERROR	*MIXED*	*NEG _CFO*	*OP_ CYCLE*	*σCFO*	*σCNOA*	*RANK_ |CNOA|*	*SIZE*	*PROFIT-ABILITY*	*GROWTH*
SIZE	−0.041	−0.033	**−0.108**	**−0.066**	**−0.084**	**−0.203**	**−0.125**		**−0.114**	−0.040
PROFITABILITY	**−0.171**	**−0.051**	−0.036	0.015	**−0.318**	**−0.449**	**−0.357**	**−0.095**		**0.115**
GROWTH	**−0.066**	**−0.276**	−0.021	**−0.097**	0.021	0.017	**0.059**	−0.034	**0.060**	

---

*,**,*** Differences across groups are significant (two-tailed), p-value ≤ 0.10, 0.05, and 0.01 levels of significance, respectively.

In Panel B, significant correlations (two-tailed p-value ≤ 0.05) shown in **bold** type.

Variable Definitions:

$ERROR_t$ = absolute value of the cash flow forecast error per share divided by average price over period t. Cash flow forecast error is the actual cash flow per share reported by I/B/E/S for period t minus the forecasted cash flow per share at period $t-1$. Forecasted cash flow per share is the mean of the first forecast made by each analyst at least four months after the prior year-end;

$MIXED_{t-1}$ = dummy variable equal to 1 if working capital accruals are negative and *CFO* (Compustat Data308) is positive, or if working capital accruals are positive and *CFO* is negative. Working capital accruals are defined as Data304 + Data305 − Data302 − Data303;

NEG_CFO_{t-1} = dummy variable equal to 1 if operating cash flow is negative, and 0 otherwise;

OP_CYCLE_{t-1} = cash operating cycle (Dechow et al. 1998), averaged across the number of years for which data are available. Operating cycle $= [\alpha + (1-\pi)\gamma - \beta(1-\pi)]$. $\alpha = (AR_t + AR_{t-1})/2S_t$; $\beta = (AP_t + AP_{t-1})/2S_t(1-\pi)$; $\pi = E_t/S_t$. $\gamma = g_1/(1-\pi)$ where g_1 is the estimated coefficient on S_t in a regression of INV_t on S_t and ΔS_t. Financial statement variables are obtained from Compustat; *AR* (accounts receivable) is Data2; *S* (sales) is Data12; *AP* (accounts payable) is (Data70 + Data153); *E* (income before extraordinary items) is Data123; and *INV* (inventory) is data3;

$PROFITABILITY_{t-5\text{ to }t}$ = average profitability over the five years ending with the forecast year calculated as *INCOME* (Data126) divided by *SALES* (Data12);

$SIZE_{t-1}$ = natural log of assets (Data6);

$RANK\_|CNOA_{t-1}|$ = decile rank of the absolute value of working capital accruals (Data304 + Data305 − Data302 − Data303) divided by market value of equity (Data54 × average price); $|CNOA|$ is ranked within the population of Compustat firms;

$\sigma CFO_{t-6\text{ to }t-1}$ = standard deviation of *CFO* (Data308) divided by average market value of equity (Data54 × average price) calculated over the five years ending with the forecast year;

$\sigma CNOA_{t-6\text{ to }t-1}$ = standard deviation of working capital accruals (Data304 + Data305 − Data302 − Data303) divided by average market value of equity (Data54 × average price) calculated over the five years ending with the forecast year;

$CNOA_{t-1}$ = working capital accruals (Data304 + Data305 − Data302 − Data303) divided by average market value of equity (Data54 × average price);

CFO_{t-1} = *CFO* (Compustat Data308) divided by average market value of equity (Data54 × average price); and

$INDUSTRY_{t-1}$ = groupings based on Compustat SIC Code (Barth, Cram, and Nelson 2001): Agriculture, mining, construction (0001–1999, except 1300–1399); Food (2000–2111); Textiles, printing, and publishing (2200–2799); Chemicals (2800–2824, and 2840–2899); Pharmaceuticals (2830–2836); Extractive industries (2900–2999, and 1300–1399); Durable manufacturers (3000–3999, except 3530–3579, and 3670–3679); Computers (7370–7379, 3570–3579, and 3670–3679); Transportation (4000–4899); Utilities (4900–4999); Retail (5000–5999); Services (7000–8999, except 7370–7379); Other (9000–9999).

The mean absolute value of the cash flow forecast error scaled by average price ($ERROR_t$) for the sample of I/B/E/S firms is 0.036. The median (0.017) is approximately half of the mean, consistent with the presence of a large number of small error firms (recall that $ERROR_t$ is greater than zero). Approximately 34 percent (66 percent) of firms exhibit $MIXED_{t-1}$ ($SAME_{t-1}$) cash flows and accruals, while only 3.3 percent of firms have negative cash flows. Thus, in contrast to our experiment, we have an unbalanced number of firms in each cell that may affect our ability to detect differences. The average OP_CYCLE_{t-1} is 0.191 years (approximately 69 days), which is slightly shorter than the average operating cycle documented by Barth, Cram, and Nelson (2001) of 0.22 years (80 days). Average $PROFITABILITY_{t-1}$ on sales is approximately 8.8 percent. The mean rank of absolute operating accruals ($RANK\_|CNOA_{t-1}|$) is 3.4, which is less that the mean rank for all Compustat firms, of 4.5. This is consistent with our exclusion of firms with significant special items. The standard deviations of cash flows and accruals are 0.080 and 0.068, respectively. Each of these measures is skewed, with the median less than the mean. Operating cash flow (CFO_{t-1}) averages 11.8 percent of the average market value of equity, while working capital accruals (CNO_{t-1}) average 1.1 percent of average market value. Average sales growth is 13.1 percent. The industry distribution of the sample cash flow forecast sample is consistent with DeFond and Hung (2003). In particular, heavy industrial firms are overrepresented and service and technology firms are underrepresented, relative to the Compustat population.

Comparisons across $MIXED_{t-1}$ and $SAME_{t-1}$ groups reveal some significant differences in mean values. A univariate test of the difference between $ERROR_t$ for $MIXED_{t-1}$ and $SAME_{t-1}$ predictions shows that the mixed sign $ERROR_t$ (0.044) is significantly higher than the same sign $ERROR_t$ (0.031, two-tailed p-value <0.01). The $MIXED_{t-1}$ group also includes more NEG_CFO_{t-1} observations (4.7 percent, compared to 2.6 percent), a longer operating cycle (0.207 compared to 0.182), lower $PROFITABILITY_{t-1}$ (8.4 percent compared to 9.1 percent) and lower growth (5.7 percent compared to 16.9 percent). We find significant differences in five out of 14 *INDUSTRY* groups. Most notably, $MIXED_{t-1}$ firms comprise more durable manufacturers and textile firms, and fewer mining and extractive firms.

The correlation matrix of regression variables presented in Panel B of Table 5 shows that forecast error is positively correlated with σCFO_{t-1} (Spearman Correlation = 0.350), $\sigma CNOA_{t-1}$ (Spearman Correlation = 0.275), and NEG_CFO_{t-1} (Spearman Correlation = 0.073). These relations are as expected—variability in historical performance measures appears to make forecasting cash flows more difficult as does forecasting negative cash flows. Extreme changes in net operating assets ($RANK\_|CNOA_{t-1}|$) in the period of the forecast are positively associated with cash flow forecast errors (Spearman Correlation = 0.200). This is consistent with Bradshaw et al.'s (2001) conjecture that analysts fail to anticipate lower levels of persistence associated with extreme values of accruals. Forecast error is negatively associated with OP_CYCLE_{t-1} (Spearman Correlation = −0.077), as expected. Forecast error is also negatively correlated with $PROFITABILITY_{t-1}$ (Spearman Correlation = −0.171), and $GROWTH_{t-1}$ (Spearman Correlation = −0.066), consistent with the conjecture that firms are more difficult to forecast during contractions. Most important to our research question, we find that $MIXED_{t-1}$ is positively correlated with forecast errors (Spearman Correlation = 0.061).

Coefficients from the estimation of Equation (1) are presented in Table 6. We estimate the coefficients using ordinary least-squares regression and present t-statistics, as well as Z-statistics using inflated standard errors for firm clustering across time. We base our inferences on the Z-statistics. Year effects are included but not tabulated. The third and fourth columns show the estimates obtained from regressing $ERROR_t$ on $MIXED_{t-1}$ and NEG_CFO_{t-1} without any of the control variables in the model. The intercept is positive and significant (coefficient of 0.031; Z-statistic of 17.63; two-tailed p-value <0.01). The coefficient on $MIXED_{t-1}$ is also significant

TABLE 6
Summary Statistics for I/B/E/S Forecast Error Regression
(897 unique firms)

$$ERROR_t = \beta_0 + \beta_1 MIXED_{t-1} + \beta_2 NEG\_CFO_{t-1} + \beta_3 OP\_CYCLE_{t-1} + \beta_4 \sigma CFO_{t-5,t} + \beta_5 \sigma CNOA_{t-5,t} + \beta_6 RANK\_|CNOA_{t-1}| + \beta_7 SIZE_{t-1} + \beta_8 PROFITABILITY_{t-1} + \beta_9 GROWTH_{t-1} + \Sigma_{j=1}^{12} \beta_{10,j} INDUSTRY_{j,t-1} + \varepsilon_t.$$

Variable	Pred.	Coeff.	t-statistic/ Z-statistic	Coeff.	t-statistic/ Z-statistic	Coeff.	t-statistic/ Z-statistic
Intercept	?	0.031	14.94 / 17.63***	0.027	2.48 / 1.46*	0.021	0.92 / 0.68
$MIXED_{t-1}$	+	0.012	3.52 / 2.81***	0.010	2.85 / 2.53***	0.008	2.19 / 1.96**
NEG_σ_{t-1}	+	0.025	2.66 / 2.53***	0.006	0.62 / 0.63	0.005	0.56 / 0.62
$OP\_CYCLE_{t-5 \text{ to } t}$	+			0.008	0.70 / 0.39	0.018	1.33 / 0.72
$\sigma CFO_{t-5 \text{ to } t}$	+			0.103	4.70 / 1.48*	0.087	3.91 / 1.29*
$\sigma CNOA_{t-5 \text{ to } t}$	+			0.061	2.81 / 0.65	0.073	3.38 / 0.80
$RANK\_\|CNOA_{t-1}\|$	+			0.003	4.64 / 3.82***	0.004	4.95 / 4.36***
$SIZE_{t-1}$	?			−0.002	−1.96 / −1.02	−0.002	−1.67 / −0.84
$PROFITABILITY_{t-5 \text{ to } t}$	?			−0.011	−0.36 / −0.27	−0.003	0.07 / 0.05
$GROWTH_{t-1}$	?			−0.017	−2.82 / −3.77***	−0.012	−1.92 / −2.85***
$INDUSTRY_{t-1}$							
Food	?					−0.019	−1.31 / −1.25
Textiles	?					−0.006	−0.42 / −0.32
Chemicals	?					0.010	0.70 / 0.50
Pharmaceuticals	?					−0.017	−1.18 / −0.99
Mining	?					−0.005	−0.53 / −0.53
Other Extractive	?					−0.015	−1.84 / −1.11
Durable Manufacturing	?					−0.019	−1.55 / −1.15
Computers	?					−0.000	−0.08 / −0.02

(continued on next page)

TABLE 6 (continued)

Variable	Pred.	Coeff.	t-statistic/ Z-statistic	Coeff.	t-statistic/ Z-statistic	Coeff.	t-statistic/ Z-statistic
Transportation	?	0.005	0.36 / 0.29				
Utilities	?					−0.002	−0.10 / −0.09
Retail	?					−0.019	−1.50 / −1.24
Services	?					−0.008	−0.59 / −0.42
Other	?					−0.005	−0.20 / −0.27
n		2,188		2,188		2,188	
Adj. R^2		0.010		0.094		0.109	

*,**,*** (one-tailed), p-value ≤0.10, 0.05, and 0.01 levels of significance, respectively. Z-scores inflate standard errors to correct for firm-level time-series clustering.

Year effects are not tabulated.

See variable definitions in Table 5.

and positive (coefficient of 0.012; Z-statistic of 2.81; one-tailed p-value <0.01) as is the coefficient on NEG_CFO_{t-1} (coefficient of 0.025; Z-statistic of 2.53; one-tailed p-value <0.01). These results are consistent with predictions.

The fifth and sixth columns present coefficients and test statistics from estimation of the model with control variables. The coefficient on the $MIXED_{t-1}$ variable remains significant (coefficient of 0.010; Z-statistic of 2.53; one-tailed p-value <0.01); however, NEG_CFO_{t-1} is no longer significant when the other control variables are included in the regression. In addition, $RANK\_|CNOA_{t-1}|$ is significantly positively related to forecast errors (coefficient of 0.003; Z-statistic of 3.82; one-tailed p-value <0.01) and $GROWTH_{t-1}$ is negatively related to forecast errors (coefficient of −0.017; Z-statistic of −3.77; one-tailed p-value <0.01). σCFO_{t-1} is positive and marginally significant (coefficient of 0.103; Z-statistic of 1.48; one-tailed p-value <0.10).

The last two columns present the regression coefficients and test statistics from estimation of the full model (i.e., including industry dummy variables). In the presence of industry controls, the intercept becomes insignificant. The variable of interest, $MIXED_{t-1}$, remains statistically significant, providing support for our theory that increased complexity caused by differences in the sign of the accruals and cash flows is associated with higher forecasting errors (coefficient of 0.008; Z-statistic of 1.96; one-tailed p-value <0.05). $RANK\_|CFOA_{t-1}|$, σCFO_{t-1}, and $GROWTH_{t-1}$ all retain their sign and level of statistical significance. None of the industry dummy variables are significantly associated with forecast errors.

Results of Analysis Based on Using Each Firm as its Own Control

Table 7 presents forecast error comparisons using a within-firm design. In Panel A of Table 7, firms that had at least one observation with $MIXED_{t-1} = 1$ and one observation with $MIXED_{t-1} = 0$ are included for analysis. Consistent with our predictions, results reveal that the forecast error is significantly higher in the firm-years where the sign was mixed ($ERROR_t = 0.042$) than in the firm-years where the sign was the same ($ERROR_t = 0.028$; t-statistic = 2.26; one-tailed p-value <0.05). The analysis in Panel B of Table 7 is similar but restricts the sample to firms with at least two mixed- and two same-sign observations in the previous 12 years. Again, the results support

TABLE 7
Within-Firm Forecast Error Comparisons

Panel A: All Firms with at Least One $MIXED_{t-1}$ and One $SAME_{t-1}$ Observation

	n	*MIXED*	*SAME*	Difference	*t*-statistic	% of Differences >0
Mean $ERROR_t$	254	0.042	0.028	0.014	2.26**	52.4

Panel B: Firms with at least two $MIXED_{t-1}$ and Two $SAME_{t-1}$ Observations

	n	*MIXED*	*SAME*	Difference	*t*-statistic	% of Differences >0
Mean $ERROR_t$	92	0.029	0.022	0.007	1.94**	57.6##

*,**,*** Significant t-statistic or Z-statistic with a one-tailed p-value ≤ 0.10, 0.05, and 0.01, respectively.
#,##,### Significant S-statistic (signed-rank test) with a one-tailed p-value ≤ 0.10, 0.05, and 0.01, respectively.
See variable definitions in Table 5.

the theory that within the same firm, firm-years with working capital and CFO of different signs have higher errors ($ERROR_t = 0.029$) than firm-years with the same sign ($ERROR_t = 0.022$; t-statistic = 1.94; one-tailed p-value < 0.05). These results suggest that analysts' forecast errors are significantly higher when the firm reports working capital accruals and CFO of different signs.

Quasi-Experimental Design: Value Line Data

The analysis in the preceding section documented an association between various firm attributes, including $MIXED_{t-1}$, and realized forecast errors. In this section, we replicate the I/B/E/S-based quasi-experiment with cash flow forecast data collected from the Value Line Investment Survey. The Value Line Investment Survey is a comprehensive source of information and ratings on approximately 1,700 publicly traded companies compiled by over 90 independent analysts. Each company report contains, among other things, Value Line's proprietary predictability measures and financial forecasts for the coming one to five years.

Value Line data have advantages and disadvantages relative to I/B/E/S data. Advantages include the availability of firm-specific proprietary measures of predictability and stability that may better control for firm attributes that give rise to prediction error, and a more stable and consistent set of firms for which cash flow forecasts are available. Disadvantages include coverage primarily limited to large firms, the availability of only one forecast per firm, and the cost of hand-collection.

To complete this analysis, we hand-collect cash flow forecast and actual data from company reports, published monthly over the period 2003–2005. We exclude from our sample firms in the banking and insurance industries because measures of operating accruals for these firms are not comparable to those in other industries. We further limit our analysis to calendar-year firms for which cash flow forecasts are available as of April 30 of each year. Value Line publishes, at most, one forecast per firm per month. We choose April 30 to allow sufficient time for analysts to incorporate into their current-year forecasts previous cash flow information contained in annual reports published during the first quarter.

We collect realized (actual) cash flows from subsequently published Value Line reports to ensure that predicted and realized cash flows are reported on the same measurement basis. We also collect Value Line's proprietary $PREDICTABILITY_{t-1}$ and $STABILITY_{t-1}$ indexes for each firm. All other financial statement data are collected from Compustat by individually cross-referencing company names and stock tickers in Compustat to those provided by Value Line. Our data collection procedure results in 591 firm-year observations with sufficient data to complete our analyses.[21] We estimate the following augmented regression with Value Line data:[22]

$$\begin{aligned} ERROR_t = {} & \beta_0 + \beta_1 MIXED_{t-1} + \beta_2 NEG\_CFO_{t-1} + \beta_3 OP\_CYCLE_{t-1} + \beta_4 \sigma CFO_{t-5,t} \\ & + \beta_5 \sigma CNOA_{t-5,t} + \beta_6 RANK\_|CNOA_{t-1}| + \beta_7 SIZE_{t-1} + \beta_8 PROFITABILITY_{t-1} \\ & + \beta_9 GROWTH_{t-1} + \beta_{10} STABILITY_{t-1} + \beta_{11} PREDICTABILITY_t \\ & + \sum_{j=1}^{12} \beta_{12,j} INDUSTRY_{j,t-1} + \varepsilon_t. \end{aligned} \tag{4}$$

All of the variables are measured as defined previously, with the exception of $ERROR_t$, $STABILITY_{t-1}$, and $PREDICTABILITY_{t-1}$. In Equation (4), $ERROR_t$ is the absolute value of the difference between the actual cash flow per share reported by Value Line for a given year and the forecasted cash flow per share predicted by Value Line analysts as of April 30 of that year. We divide the difference by the average market value of equity over the forecast period. $STABILITY_{t-1}$ is a measure of the stability of the stock's price. This index ranges from 5 to 100, with 5 representing the lowest level of stability. According to Value Line, $STABILITY_{t-1}$ includes sensitivity to the market (beta) as well as the firm's inherent volatility. We expect a negative coefficient on $STABILITY_{t-1}$ to the extent that systematic and unsystematic risk factors are negatively related to cash flow predictability. $PREDICTABILITY_{t-1}$ is an index that measures the reliability of forecasts based on the stability of year-to-year comparisons. The index ranges from 5 to 100, where 5 represents the lowest level of predictability and 100 the highest. We expect a negative coefficient on $PREDICTABILITY_{t-1}$.

---

[21] Forecasts made in 2003 and 2004 are paired with actual realizations reported in 2004 and 2005, respectively.

[22] Because we collected only three years of Value Line data, we do not have a sufficiently long time-series to perform a meaningful within-firm analysis.

Results of the Quasi-Experiment: Value Line Data

Panel A of Table 8 presents descriptive statistics for the sample of Value Line firms used in the archival analysis. The mean absolute value of the cash flow forecast error scaled by average price ($ERROR_t$) for the sample of Value Line firms is 0.017. This is lower than that of the I/B/E/S sample (0.034) and is likely an artifact of Value Line's propensity to cover larger, better-known firms. Approximately 27.5 percent (72.5 percent) of firms exhibit $MIXED_{t-1}$ ($SAME_{t-1}$) cash flows and accruals in the Value Line sample, while 5.9 percent of firms have negative cash flows. The average OP_CYCLE_{t-1} is 0.190 years (approximately 69 days). The standard deviations of cash flows and accruals are 0.096 and 0.089, respectively. Each of these measures is skewed, with a median less than the mean. The mean rank of absolute operating accruals $RANK\_|CNOA_{t-1}|$) is 4.0, which is less than the mean rank for all Compustat firms, of 4.5. Operating cash flow (CFO) averages 11.2 percent of the average market value of equity, while working capital accruals ($CNOA_{t-1}$) average 2.7 percent of average market value. Average sales growth is 15.3 percent. Most of these firm attribute values are consistent with the I/B/E/S sample, except for $CNOA_{t-1}$, $\sigma CNOA_{t-1}$, NEG_CFO_{t-1}, and σCFO_{t-1}, which are each higher. This suggests that that the sample of Value Line firms has more volatile accruals and cash flows than the I/B/E/S sample.

The mean sample $PREDICTABILITY_{t-1}$ and $STABILITY_{t-1}$ index values of 50.58 and 53.816, respectively, are approximately equal to the midpoint of the scale, which ranges from 5 to 100 for each measure. This suggests that sample firms have average predictability and stability, despite their accrual and cash flow volatility. The industry distribution of the Value Line forecast sample is generally consistent with the I/B/E/S sample, with the exception that the Value Line sample contains more services firms.

Comparisons across $MIXED_{t-1}$ and $SAME_{t-1}$ groups reveal significant differences in mean values. A univariate test of the difference between $ERROR_t$ for $MIXED_{t-1}$ and $SAME_{t-1}$ predictions shows that the mixed sign $ERROR_t$ (0.023) is significantly higher than the same sign $ERROR_t$ (0.015, one-tailed p-value <0.01). The $MIXED_{t-1}$ group also includes more NEG_CFO observations (14.1 percent, compared to 2.8 percent), and marginally lower $GROWTH$ (12.8 percent compared to 16.3 percent, one-tailed p-value <0.10). We find mostly marginal differences in four out of 14 $INDUSTRY$ groups. Most notably, $MIXED_{t-1}$ firms comprise more durable manufacturers and computer firms, and fewer extractive firms.

The correlation matrix of regression variables presented in Panel B of Table 8 shows that forecast error is positively correlated with $MIXED_{t-1}$ (Spearman Correlation $= 0.091$), consistent with our predictions and the results from Table 5, Panel B. Forecast error is also positively correlated with NEG_CFO_{t-1} (Spearman Correlation $= 0.110$), σCFO_{t-1} (Spearman Correlation $= 0.295$), $\sigma CNOA_{t-1}$ (Spearman Correlation $= 0.235$), and extreme changes in net operating assets ($RANK\_|CNOA_{t-1}|$) (Spearman Correlation $= 0.178$). These results are as expected and consistent

TABLE 8

Descriptive Statistics for Value Line Data

Panel A: Distributional Statistics for Regression Variables

	All Observations					Means by Group	
Variable	Mean	Std. Dev.	Q1	Median	Q3	Mixed Sign	Same Sign
$ERROR_t$	0.017	0.023	0.003	0.009	0.021	0.023	0.015***
$MIXED_{t-1}$	0.275	0.447					
NEG_CFO_{t-1}	0.059	0.236				0.141	0.028***
$OP\_CYCLE_{t-5\text{ to }t}$	0.190	0.138	0.097	0.169	0.257	0.196	0.191
$\sigma CFO_{t-5\text{ to }t}$	0.096	0.171	0.035	0.053	0.087	0.116	0.089*
$\sigma CNOA_{t-5\text{ to }t}$	0.089	0.168	0.023	0.044	0.082	0.103	0.084
$RANK\_\|CNOA_{t-1}\|$	4.003	2.487	2.000	4.000	6.000	3.681	4.126**
$SIZE_{t-1}$	7.405	1.180	6.610	7.310	8.185	7.363	7.422
$PROFITABILITY_{t-5\text{ to }t}$	0.077	0.045	0.047	0.067	0.100	0.075	0.078
$GROWTH_{t-1}$	0.153	0.231	0.047	0..114	0.197	0.128	0.163*
CFO_{t-1}	0.112	0.109	0.056	0.093	0.145	0.125	0.108*
$CNOA_{t-1}$	0.027	0.083	−0.001	0.015	0.043	0.013	0.043***
$STABILITY_{t-1}$	53.816	27.014	30.000	50.000	80.000	48.343	55.900*
$PREDICTABILITY_{t-1}$	50.575	28.186	25.000	50.000	75.000	43.589	53.236***
$INDUSTRY_{t-1}$							
Agriculture	0.003					0.000	0.004
Food	0.019					0.012	0.021
Textiles	0.079					0.074	0.081
Chemicals	0.051					0.055	0.049
Pharmaceuticals	0.034					0.024	0.037
Mining	0.076					0.074	0.077
Other Extractive	0.056					0.031	0.065*
Durable Manufacturing	0.343					0.405	0.320**
Computers	0.071					0.104	0.058*
Transportation	0.058					0.061	0.056
Utilities	0.110					0.117	0.107
Retail	0.100					0.085	0.105
Services	0.101					0.080	0.110
Other	0.005					0.000	0.007*
n	591					163	428

Panel B: Pearson (above the diagonal) and Spearman (below the diagonal) Correlations ($n = 591$)

	$ERROR$	$MIXED_{t-1}$	NEG_CFO_{t-1}	$OP\_CYCLE_{t-5\text{ to }t}$	$\sigma CFO_{t-5\text{ to }t}$	$\sigma CNOA_{t-5\text{ to }t}$	$RANK\_\|CNOA_{t-1}\|$	$SIZE_{t-1}$	$PROFITABILITY_{t-5\text{ to }t}$	$GROWTH_{t-1}$	CFO_{t-1}	$CNOA_{t-1}$	$STABILITY_{t-1}$	$PREDICTABILITY_{t-1}$
$ERROR_t$		0.085	0.083	0.065	0.089	0.062	0.162	−0.244	−0.119	−0.034	0.061	0.021	0.029	−0.163
$MIXED_{t-1}$	0.091		0.214	0.017	0.070	0.051	−0.080	−0.023	−0.031	−0.067	0.070	−0.301	0.125	−0.153
NEG_CFO_{t-1}	0.110	0.214		0.120	0.058	0.079	0.184	−0.118	−0.021	0.007	−0.324	0.106	0.200	−0.196
$OP\_CYCLE_{t-5\text{ to }t}$	0.021	0.036	0.114		0.038	0.092	0.094	−0.134	−0.015	−0.029	−0.246	0.055	0.193	−0.001
$\sigma CFO_{t-5\text{ to }t}$	0.295	0.085	0.113	−0.120		0.875	0.208	0.102	−0.177	−0.028	0.179	0.061	0.048	−0.055
$\sigma CNOA_{t-5\text{ to }t}$	0.235	0.066	0.157	0.121	0.719		0.294	0.096	−0.263	0.006	0.098	0.149	0.102	−0.065
$RANK\_\|CNOA_{t-1}\|$	0.178	−0.089	0.177	0.079	0.379	0.496		0.041	−0.332	0.180	0.069	0.306	0.141	−0.183
$SIZE_{t-1}$	−0.365	−0.044	−0.124	−0.193	0.148	0.084	0.046		−0.115	0.117	0.293	0.003	0.278	0.019
$PROFITABILITY_{t-5\text{ to }t}$	−0.181	−0.048	−0.004	0.038	−0.416	−0.478	−0.359	−0.100		0.073	−0.121	−0.126	0.055	0.032

(continued on next page)

TABLE 8 (continued)

$GROWTH_{t-1}$	−0.056	**−0.200**	0.003	0.036	0.024	**0.088**	**0.253**	**0.111**	0.033		−0.001	0.076	0.079	−0.082
CFO_{t-1}	0.060	0.036	−0.371	**−0.376**	**0.346**	**0.068**	0.027	**0.350**	−0.142	−0.078		**−0.125**	0.080	−0.127
$CNOA_{t-1}$	0.032	**−0.578**	0.057	0.034	**0.126**	**0.236**	**0.595**	0.024	**−0.145**	**0.342**	**−0.114**		0.009	0.022
$STABILITY_{t-1}$	**−0.116**	−0.123	**−0.197**	−0.211	**−0.126**	−0.176	−0.136	**0.305**	0.017	**−0.098**	**0.258**	0.023		**0.499**
$PREDICTABILITY_{t-1}$	**−0.175**	−0.151	**−0.195**	−0.006	**−0.312**	−0.299	**−0.178**	0.037	0.039	−0.028	−0.030	0.037	**0.495**	

---

*,**,*** Differences across groups are significant (two-tailed), p-value ≤ 0.10, 0.05, and 0.01 levels of significance, respectively.

In Panel B, Significant correlations (p-value <0.05) shown in **bold** type.

Variable Definitions:

$STABILITY_{t-1}$ = Value Line's price stability index. A measure of the stability of a stock's price, including sensitivity to the market (beta) as well as the firm's inherent volatility, ranging from lowest stability of 5 to highest stability of 100; and

$PREDICTABILITY_{t-1}$ = Value Line's earnings predictability index. A measure of the reliability of forecasts based on the stability of year-to-year comparisons, ranging from lowest predictability of 5 to highest predictability of 100.

For other variable definitions, see Table 5.

with the I/B/E/S sample. Forecast error is negatively correlated with $PROFITABILITY_{t-1}$ (Spearman Correlation = −0.181), which is also consistent with the I/B/E/S sample.

Importantly, we find that $STABILITY_{t-1}$ and $PREDICTABILITY_{t-1}$ are each negatively correlated with $ERROR_t$ (Spearman Correlations of −0.116 and −0.175, respectively), suggesting that lower predictability leads to higher forecast errors. As well, we find that these proprietary measures are negatively correlated with all of the firm attributes posited to decrease predictability, including $MIXED_{t-1}$ and NEG_CFO_{t-1}. This suggests the need for multivariate regression to determine whether $MIXED_{t-1}$ and NEG_CFO_{t-1} are subsumed by Value Line's measures of $STABILITY_{t-1}$ and $PREDICTABILITY_{t-1}$.

Table 9 presents results from our estimation of Equation (4). We estimate the coefficients using ordinary least-squares regression and present t-statistics, as well as Z-statistics using inflated standard errors for firm clustering across time. We base our inferences on the Z-statistics. Year effects are included, but not tabulated. The third and fourth columns present estimates obtained from regressing $ERROR_t$ on $MIXED_{t-1}$ and NEG_CFO_{t-1} without any of the control variables in the model. The intercept is positive and significant (coefficient of 0.015; Z-statistic of 14.92; one-tailed p-value <0.01). The coefficient on $MIXED_{t-1}$ is also significant and positive (coefficient of 0.006; Z-statistic of 2.14; one-tailed p-value <0.05) as is the coefficient on NEG_CFO_{t-1} (coefficient of 0.011; Z-statistic of 1.86; one-tailed p-value <0.05). These findings provide support for our theory that increased complexity is associated with higher forecasting errors.

The last two columns present coefficients and test statistics from estimation of the model with control variables. In the presence of control variables, the intercept becomes insignificant. The coefficient on the $MIXED_{t-1}$ variable remains significant (coefficient of 0.005; Z-statistic of 2.01; one-tailed p-value <0.05); however, NEG_CFO_{t-1} becomes insignificant. This indicates that Value Line's proprietary predictability measures do not subsume our proxy for informational complexity. $RANK\_|CNOA_{t-1}|$ is significantly positively related to forecast errors (coefficient of 0.001; Z-statistic of 2.68; one-tailed p-value <0.01) as is σCFO_{t-1} (coefficient of 0.027; Z-statistic of 2.01; one-tailed p-value <0.05). Value Line's proprietary measure of $PREDICTABILITY_{t-1}$ is significantly negatively related to forecast errors (coefficient of −0.000; Z-statistic of −2.62; one-tailed p-value <0.05), while $STABILITY_{t-1}$ is marginally negatively related to forecast error (coefficient of −0.000; Z-statistic of −1.44; one-tailed p-value <0.10).

VI. SUMMARY AND CONCLUSION

Plumlee (2003) reports that analysts' forecast errors are positively related to the complexity of forecast-relevant information. We extend her work by proposing that two features of the information contained in the operating-activities section of the indirect-approach statement of cash flows can contribute to forecasting complexity. First, we show that the currently required structure of the operating-activities section of the indirect-approach statement of cash flows—when compared to an alternative, forward-order format that conforms more closely to the positively related, intertemporal behavior of accruals and cash flows—causes lower levels of learning and higher levels of forecast error and dispersion. However, we note that the results related to higher levels of forecast error are primarily driven by the unusual combination of negative cash flow and positive accrual firms, but the findings related to forecast dispersion are robust across both positive and negative cash flow firms.

Second, we show that the offsetting (i.e., "mixed sign") pattern of operating cash flows and operating accruals information reported by most companies also impedes investors' ability to learn the time-series properties of operating cash flows and operating accruals. While we find that mixed-sign forecast inputs lead to significantly higher cash flow forecast errors and forecast

TABLE 9

Summary Statistics for Value Line Forecast Error Regression

$$ERROR = \beta_0 + \beta_1 MIXED_{t-1} + \beta_2 NEG\_CFO_{t-1} + \beta_3 OP\_CYCLE_{t-1} + \beta_4 \sigma CFO_{t-5,t} + \beta_5 \sigma CNOA_{t-5,t} + \beta_6 RANK\_|CNOA_{t-1}| + \beta_7 SIZE_{t-1} + \beta_8 PROFITABILITY_{t-1} + \beta_9 GROWTH_{t-1} + \beta_{10} STABILITY_{t-1} + \beta_{11} PREDICTABILITY_t + \Sigma_{j=1}^{12} \beta_{12,j} INDUSTRY_{j,t-1} + \varepsilon_t.$$

Variable	Pred.	Coeff.	t-statistic/Z-statistic	Coeff.	t-statistic/Z-statistic
Intercept	?	0.015	13.56***/14.92***	0.013	1.21 / 1.18
$MIXED_{t-1}$	+	0.006	2.57***/2.14**	0.005	2.23**/2.01**
NEG_CFO_{t-1}	+	0.011	2.77***/1.86**	0.007	1.70**/1.17
$OP\_CYCLE_{t-5 \text{ to } t}$	+			−0.001	−0.13 / −0.13
$\sigma CFO_{t-5 \text{ to } t}$	+			0.027	2.32**/2.01**
$\sigma CNOA_{t-5 \text{ to } t}$	+			−0.029	−2.37 / −2.32
$RANK\_|CNOA_{t-1}|$	+			0.001	2.49***/2.68***
$SIZE_{t-1}$	?			0.001	1.17 / 1.13
$PROFITABILITY_{t-5 \text{ to } t}$	?			−0.024	−0.96 / −1.02
$GROWTH_t$	?			0.001	0.27 / 0.29
$STABILITY_{t-1}$	−			−0.000	−1.53*/−1.44*
$PREDICTABILITY_t$	−			−0.000	−2.65**/−2.62**
$INDUSTRY_{t-1}$					
Food	?			0.025	2.29**/2.00**
Textiles	?			0.006	0.73 / 0.69
Chemicals	?			0.005	0.51 / 0.45
Pharmaceuticals	?			−0.002	−0.17 / −0.17
Mining	?			0.008	1.03 / 0.86
Other Extractive	?			0.005	0.78 / 0.72
Durable Manufacturing	?			0.004	0.48 / 0.45
Computers	?			−0.008	−1.91*/−2.12**
Transportation	?			−0.000	0.61 / 0.60
Utilities	?			−0.002	−0.04 / −0.04
Retail	?			0.002	−0.21 / −0.20
Services	?			0.018	0.28 / 0.27
Other	?			−0.003	−1.47 / 0.98
n		591		591	
Adj. R^2		0.027		0.108	

*,**,*** (one-tailed), p-value ≤ 0.10, 0.05, and 0.01 levels of significance, respectively.
Year effects are not tabulated.
See variable definitions in Table 5.

dispersion across both forecast conditions, the forecast errors from the mixed-sign inputs are highest in the currently mandated reverse-order indirect-approach statement of cash flows.

We also report the results of a quasi-experimental analysis of publicly available cash flow forecasts provided by I/B/E/S and Value Line analysts. Inferences from this analysis are consistent with inferences drawn from the experiment and support our hypotheses about the complexity of mixed-sign forecast inputs. Specifically, after controlling for differences across firm attributes commonly associated with the accuracy of analysts' forecasts, we find that forecast errors are higher for companies that report mixed-sign operating cash flows and operating accruals information. These results suggest that cognitive limitations that impede information acquisition may manifest as systematic errors in a market setting.

This study extends prior research on the effects of alternative financial reporting classification, measurement, and presentation schemes on financial statement users' learning and judgment processes (e.g., Dietrich et al. 2001). In this study, we provide evidence that is directly relevant to questions regarding the form and content of an important performance statement. Obtaining a better understanding of financial statement users' information acquisition processes will help to inform the deliberations of standard-setters seeking to weigh the costs and benefits of proposed financial statement disclosure requirements. Interestingly, the "reverse" presentation format for the operating section of the indirect-approach statement of cash flows is often derided as confusing by students, accounting educators, and users of financial statements (see, e.g., Stice et al. 2004, 245; Stickney and Weil 2003, 184)[23] and is opposite of the predictive, future-oriented perspective taken in most conceptual descriptions of the balance sheet elements and the accruals process (e.g., FASB 1985).

Our study also illustrates an unintended consequence of giving primacy to reported net income in the reconciliation between cash flows and accruals. The results of this study should be useful to standard-setters as they reconsider the structure of performance reporting and the prominence currently afforded accrual-basis net income across currently required performance reports. In particular, accrual-basis net income is (1) the focus of the statement of earnings, (2) the numerator in the only ratio required by generally accepted accounting principles (i.e., earnings per share), (3) the first item included in the determination of comprehensive income, and (4) the first item presented in the indirect-approach statement of cash flows. However, because net income is not defined in the conceptual framework, it is one of an infinite number of ill-defined, potentially reportable, arbitrary partitions of the change in net assets during a given period.

Caveats and Future Research

Although we believe the comparative advantages of experiments are particularly well suited to the research questions in this study (Libby et al. 2002), critics of experiments-based research occasionally suggest that documented empirical findings in experiments are caused by under-motivated participants in idiosyncratic, vacuum-like laboratory settings producing results that cannot sustain in market settings. Our analysis attempts to mitigate these concerns by (1) providing our participants with accuracy-based compensation and cumulative, forecast-by-forecast feedback and (2) supplementing our experimental results with a quasi-experimental archival analysis of publicly released cash flow forecasts.

---

[23] In some cases, textbooks will supplement the detailed lists with a discussion of the rationale for indirect-approach statement of cash flows operating-section adjustments that are unrelated to the expected timing of cash receipts and disbursements. For example, Harrison and Horngren (2004) provide this explanation for the "reverse" adjustment for increases in operating assets: "An increase in a current asset other than cash indicates a decrease in cash. That's because it takes cash to acquire assets."

The outcome-feedback mechanism operationalized in our experiment is more transparent than those appearing in real-world financial-forecasting settings and is more comprehensive and informationally complete than the outcome feedback appearing in similar accounting-related experiments (e.g., Luft and Shields 2001; Bloomfield et al. 2003). Indeed, the form of outcome feedback included in the present study has informational properties (i.e., single source, no delay, and linear) that typically yield the highest levels of learning in prior research (Diehl and Sterman 1995). Therefore, we propose that these directional-format effects in financial-forecasting tasks may have an even greater chance of sustaining in real-world environments where feedback mechanisms do not possess these optimal properties.

In contrast to the feedback mechanism, we made other research-design choices that may diminish the likelihood that our documented directional-format effects sustain in non-laboratory (i.e., real-world) settings. For example, as discussed previously, we included a black box on the "Statement of Cash Flows Screens" (see Figure 1) instead of providing participants with a total for operating earnings. We made this choice because we were interested in isolating and investigating the effects of directional-information format on financial statement users' ability to process accounting information and we provided evidence in this paper that the black box did not affect one treatment group more than the other. However, these caveats do not address a legitimate question: What would happen if we were to include a numerical total for net earnings, along with the cash and accrual information? Given the design of our study, we cannot provide an answer to the question; however, we offer two conjectures.

First, to the extent that forecasters remove some portion of forecast weight from the two diagnostic cues (i.e., CFO_t and $Accruals_t$) and place it on the aggregate, informationally redundant cue (i.e., OE_t), accruals information will be overweighted in forecast judgments.[24] Based on a simple, logical extension, accruals overweighting could lead to higher levels of forecast error for all format conditions, potentially diminishing the ability to detect differences between the conditions. However, we also conjecture that our design choice might lead to an interesting unintended (and, in this study, uninvestigated) consequence related to forecasts of OE_{t+1}. In particular, if users have grown accustomed to the reverse-order statements in their forecast of future operating earnings, then the cash-flow-statement adjustment may serve as a short-cut cue used to qualify their use of current period operating earnings (e.g., negative accruals adjustment is "good news").[25] While we conjecture that the presence of net income is more likely to have a negative effect on cash flow forecast accuracy and note that the reverse-accruals adjustment for net-income forecasts also becomes highly complex when there are multiple accruals items, we cannot rule out the possibility of improved operating-earnings-forecast accuracy under the current reversed-accruals cash-flow-statement format. We propose that further investigation of the effects of reported operating earnings and forecasts of operating earnings is warranted.

Another design choice that potentially affects the generalizability of our study is our use of a single, highly summarized accruals measure in our "Statement of Cash Flows Screens" (see Figure 1). Given the different empirically observed weights and signs of each accruals component in real-world settings (Barth, Cram, and Nelson 2001), including multiple line items of accruals information will certainly increase the complexity of the cash-flow-forecast learning task. We believe such an increase in task complexity would uniformly increase the noise in participants' forecasts, thereby increasing the likelihood of making Type II errors in statistical inferences (i.e., task complexity would become so great that no differences between forward-order and reverse-order could be detected). However, as we noted at the beginning of this paper, the forward-order format for the statement of cash flows more closely conforms to the semantic, sequential, and causal structure of a cash-flow-generation process. To the extent knowledge of this causal model is more fully activated or easier to apply under the forward-order format (Farrell et al. 2007; Vera-Muñoz et al. 2007), forecast performance under the forward-order format should result in even better relative performance than that documented in the present study. Given the significant potential changes in financial statement format that may result from the FASB's and IASB's current projects on Financial Statement Presentation (FASB 2007), each of our design choices warrant careful investigation in future research.

---

[24] Recall from Table 2, Panel A, the implicit "true" model weights for CFO_t and $Accruals_t$ are $\beta_1 = 1.00$ and $\beta_2 = 0.55$, respectively. Using OE_t, in a random walk fashion, would results in applied model weights of $\beta_1 = \beta_2 > 0.55$ for CFO_t and $Accruals_t$, respectively.

[25] We thank Rob Bloomfield for this observation.

REFERENCES

American Institute of Certified Public Accountants (AICPA). 2005. In *Accounting Trends and Techniques*, 59th edition, edited by Y. Iofe. New York, NY: AICPA.

Barth, M. E., D. P. Cram, and K. K. Nelson. 2001. Accruals and the prediction of future cash flows. *The Accounting Review* 76 (1): 27–58.

——, R. Kasznik, and M. F. McNichols. 2001. Analyst coverage and intangible assets. *Journal of Accounting Research* 39 (1): 1–34.

Bloomfield, R. J., R. Libby, and M. W. Nelson. 2003. Do investors overrely on old elements of the earnings time-series? *Contemporary Accounting Research* 20 (Spring): 1–31.

Bonner, S. E. 1999. Judgment and decision-making research in accounting. *Accounting Horizons* 13 (December): 385–399.

Bradshaw, M. T., S. A. Richardson, and R. G. Sloan. 2001. Do analysts and auditors use information in accruals? *Journal of Accounting Research* 39 (1): 45–74.

Brehmer, B. 1973. Single-cue probability learning as a function of the sign and magnitude of the correlation between cue and criterion. *Organizational Behavior and Human Performance* 9 (3): 377–395.

——. 1974. Hypotheses about relations between scaled variables in the learning of probabilistic inference tasks. *Organizational Behavior and Human Performance* 11 (1): 1–27.

——, J. Kuylenstierna, and J. Liljergren. 1974. Effects of function form and cue validity on the subjects' hypotheses in probabilistic inference tasks. *Organizational Behavior and Human Performance* 11 (3): 338–354.

——. 1979. Note on hypothesis testing in probabilistic inference tasks. *Scandinavian Journal of Psychology* 20 (1): 155–158.

Conover, W. J., M. E. Johnson, and J. K. Loebbecker. 1981. A comparative study of tests for homogeneity of variances, with applications to the outer continental shelf bidding data. *Technometrics* 23 (4): 351–361.

——. 1999. *Practical Nonparametric Statistics*. 3rd edition. New York, NY: John Wiley & Sons, Inc.

Deane, D., K. Hammond, and D. Summers. 1972. Acquisition and application of knowledge in complex inference tasks. *Journal of Experimental Psychology* 92 (1): 20–26.

Dechow, P. M., S. P. Kothari, and R. L. Watts. 1998. The relation between earnings and cash flows. *Journal of Accounting and Economics* 25 (2): 133–168.

DeFond, M. L., and M. Hung. 2003. An empirical analysis of analysts' cash flow forecasts. *Journal of Accounting and Economics* 35 (April): 73–100.

Diehl, E., and J. D. Sterman. 1995. Effects of feedback complexity on dynamic decision making. *Organizational Behavior and Human Decision Processes* 62 (May): 198–215.

Dietrich, J. R., S. J. Kachelmeier, D. N. Kleinmuntz, and T. J. Linsmeier. 2001. Market efficiency, bounded rationality, and supplemental business reporting disclosures. *Journal of Accounting Research* 39 (September): 243–269.

Easley, D., and M. O'Hara. 2004. Information and the cost of capital. *The Journal of Finance* 59 (4): 1553–1584.

Elgers, P. T., M. H. Lo, and R. J. Pfeiffer, Jr. 2003. Analysts' vs. investors' weightings of accruals in forecasting annual earnings. *Journal of Accounting and Public Policy* 22: 255–280.

Elliott, W. B., F. Hodge, J. J. Kennedy, and M. Pronk. 2007. When are graduate students a reasonable proxy for nonprofessional investors? *The Accounting Review* 82 (January): 139–168.

Farrell, A., J. Luft, and M. Shields. 2007. Accuracy in judging the nonlinear effects of cost and profit drivers. *Contemporary Accounting Research*: 24.

Financial Accounting Standards Board (FASB). 1985. *Elements of Financial Statements*. Statement of Financial Accounting Concepts No. 6. Stamford, CT: FASB.

———. 1987. *Cash Flows*. Statement of Financial Accounting Standards No. 95. (Stamford, CT: FASB.

———. 1997. *Reporting Comprehensive Income*. Statement of Financial Accounting Standards No. 130. Stamford, CT: FASB.

———. 2007. *Project Updates: Financial Statement Presentation*. Joint Project of the Financial Accounting Standards Board and International Accounting Standards Board Revised September 11, 2007. Available at: http://www.fasb.org/project/fin_stmt_presentation-scope.shtml#tentative_decisions.

Fligner, M. A., and T. J. Killeen. 1976. Distribution-free two-sample tests for scale. *Journal of the American Statistical Association* 71 (353): 210–213.

Francis, J., and M. Smith. 2005. A reexamination of the persistence of accruals and cash flows. *Journal of Accounting Research* 43 (3): 413–451.

Harrison, W. T., Jr., and C. T. Horngren. 2004. *Financial Accounting*. 5th edition. Upper Saddle River, NJ: Pearson Education, Inc.

Healy, P., A. Hutton, and K. Palepu. 1999. Stock performance and intermediation changes surrounding sustained increases in disclosure. *Contemporary Accounting Research* 16 (3): 485–520.

Hirst, D. E., P. E. Hopkins, and J. M. Wahlen. 2004. Fair values, comprehensive income reporting, and bank analysts' risk and valuation judgments. *The Accounting Review* 79 (2): 455–474.

Hong, H., J. C. Stein, and J. Yu. 2007. Simple forecasts and paradigm shifts. *The Journal of Finance* 62 (3): 1207–1242.

Libby, R., R. J. Bloomfield, and M. W. Nelson. 2002. Experimental research in financial accounting. *Accounting, Organizations and Society* 27 (October): 775–810.

Luft, J., and M. Shields. 2001. Why does fixation persist? Experimental evidence on the judgment performance effects of expensing intangibles. *The Accounting Review* 76 (October): 561–587.

Maines, L. A., and L. S. McDaniel. 2000. Effects of comprehensive-income characteristics on nonprofessional investors' judgments: The role of financial statement presentation format. *The Accounting Review* 75 (2): 179–208.

Miller, G. A. 1956. The magical number seven, plus or minus two: Some limits on our capacity for processing information. *Psychological Review* 63: 81–97.

Muchinsky, P. M., and A. L. Dudycha. 1975. Human inference behavior in abstract and meaningful environments. *Organizational Behavior and Human Performance* 13: 377–391.

Naylor, J., and R. Clark. 1968. Intuitive inference strategies in interval learning tasks as a function of validity magnitude and sign. *Organizational Behavior and Human Performance* 3 (4): 378–399.

Phillips, F., R. Libby, and P. A. Libby. 2005. *Fundamentals of Financial Accounting*. New York, NY: McGraw-Hill Irwin.

Plumlee, M. A. 2003. The effect of information complexity on analysts' use of that information. *The Accounting Review* 78 (1): 275–296.

Revsine, L., D. W. Collins, and W. B. Johnson. 2005. *Financial Reporting & Analysis*, 3rd. ed. Upper Saddle River, NJ: Pearson Prentice Hall.

Simon, H. A. 1982. *Models of Bounded Rationality: Behavioral Economics and Business Organizations*. Vol. 2. Cambridge, MA: MIT Press.

Sloan, R. G. 1996. Do stock prices fully reflect information in accruals and cash flows about future earnings? *The Accounting Review* 71 (July): 289–316.

Sniezek, J. 1986. The role of variable labels in cue probability learning tasks. *Organizational Behavior and Human Decision Processes* 38 (2): 141–161.

Stice, E. K., J. D. Stice, and K. F. Skousen. 2004. *Intermediate Accounting*. 15th edition. Mason, OH: South-Western.

Stickney, C. P., and R. L. Weil. 2003. *Financial Accounting: An Introduction to Concepts, Methods and Uses.* 10th edition. Mason, OH: South-Western.

Vera-Muñoz, S. C., M. Shackell, and M. Buehner. 2007. Accountants' usage of causal business models in the presence of benchmark data: A note. *Contemporary Accounting Research* 24 (Fall): 1015–1038.

THE ACCOUNTING REVIEW
Vol. 83, No. 4
2008
pp. 957–995

American Accounting Association
DOI: 10.2308/accr.2008.83.4.957

Determinants and Consequences of Firm Information Technology Budgets

Kevin W. Kobelsky
Baylor University

Vernon J. Richardson
University of Arkansas

Rodney E. Smith
California State University, Long Beach

Robert W. Zmud
University of Oklahoma

ABSTRACT: For most firms, the information technology (IT) budget represents a major element in the overall firm budget, and IT budget decisions often have significant operational and strategic impacts on the business processes in the firm's value chain. In this paper we use a large unique data set to examine the extent to which IT budgets are affected by environmental, organizational, and technological circumstances. We find that our cross-sectional model explains substantial variance in IT budgets, which indicates that contingent environmental, organizational, and technological factors affect managers' budget decisions. We then examine the extent to which these IT budget levels are related to future firm performance, measured using both broad financial accounting measures, such as operating profit margins and return on assets, and market returns. We find that IT budget levels are positively associated with subsequent firm performance and shareholder returns. We further suggest that IT's aggregate effect on performance is a weighted average of two very different components: (1) context-driven IT budget levels, which reflect the effects of environmental, organization, and technological factors and the IT budgets resulting from them, and (2) idiosyncratic IT budget levels, which reflect the effect of any marginal firm-specific IT budget expenditures after controlling for these contextual factors. Both components are positively associated with performance, indicating that the specified contextual factors provide an incomplete explanation of firms' value-relevant IT expenditures. The current study contributes to the

---

We thank Bruce Dehning, Kevin Dow, Charlene Henderson, Jim Hunton, Michael Mosebach, Nigel Melville, Alex Nikitkov, Gary Peters, Robin Poston, Marilyn Prosch, Brad Tuttle, Chris Wolfe, Bill McCarthy (editor) and two anonymous referees for their comments as well as participants of the 2007 AAA Annual Meeting, the 2002 International Conference on Information Systems, Korean University, the University of Waterloo, and the University of Arkansas Accounting Workshop. Earlier versions of this paper were also presented at Fudan University and Gadjah Mada University Accounting Workshops.

Editor's note: This paper was accepted by William E. McCarthy.

Submitted: May 2006
Accepted: December 2007
Published Online: July 2008

accounting information systems and management accounting literatures by assessing the causes and consequences of IT budgets.

Keywords: *IT budgets; firm performance; resource allocation.*

Data Availability: *From publicly available data sets.*

I. INTRODUCTION

Over the last three decades, firms increased spending on information technology (IT) hardware and software from 5 percent of non-residential fixed investment in 1978 to 22 percent in 2005, totaling $283 billion—approaching investments in land and structures (Bureau of Economic Analysis 2007). Despite this substantial growth in IT spending, the contributions of IT to business value remain uncertain (Brynjolfsson and Hitt 1998; Chan 2000; Santhanam 2003; Kearns 2004; Bhatt and Grover 2005). As a result, senior managers continue to question whether their firms are spending too much or too little on IT (Ross and Weill 2002; Lee and Bose 2002).

In this paper we use IT budget data for a group of large IT spending firms, known as the *InformationWeek* 500 (*InformationWeek* 2001), to investigate three related questions: (1) what contextual factors influence managers' allocations of resources to IT, (2) is there a relationship between IT budgets and firm performance, and (3) does spending more or less on IT than other similarly positioned firms affect performance?[1] Building on accounting and information systems research, we model IT budget levels as contingent upon a set of environmental, organizational, and technological factors that affect the firm's opportunity space. We use this model to separate the actual IT budget into two components: the amount expected given the firm's context (predicted IT), and any excess or shortfall (residual IT). The relation between predicted IT and performance incorporates both IT's and contextual variables' effects on performance. The relation between residual IT and performance reflects marginal returns to IT budget allocations.

For most firms, the IT budget represents a sizeable component of the overall firm budget. IT budgets include expenditures directly associated with a firm's IT function, i.e., for IT staff salaries, payments to vendors and services firms, hardware/software upgrades and replacements, training of IT staff and system users, and new development associated with systems software and application software portfolios. Thus, IT budgets support many, if not most, of a firm's requests for IT services. IT budgets that are too constrained inhibit firms' abilities to meet new service requests and fully to leverage installed technology. IT budgets that are too slack encourage the inefficient use of firms' assets.

Despite the importance of the IT budget to most firms, little prior research has investigated the factors affecting managers' IT budget allocations. In the information systems (IS) field, only Dewan et al.'s (1998) study, which investigated how contextual factors (specifically market diversification, growth and vertical integration) affect the level of IT capital investment, provides empirical evidence regarding factors likely to influence IT budget levels. A firm's IT capital investment, however, differs from its IT department budget in numerous ways (e.g., annualized versus cumulative expenses, scope of activities involved, and source of funding).

---

[1] While not all IT spending is reflected in the IT departmental budget figures reported by *InformationWeek*, the reported figures are generally representative of payment streams to vendors and services firms, the salaries of a firm's IT professionals, and a substantial portion of new IT-related capital expenditures.

Considerable research attempts to link IT spending with firm performance. Since the early 1990s, more than 50 studies have examined facets of the relationship between IT spending and productivity (i.e., real output for a given total cost).[2] A majority of these firm-level studies conclude that gross returns to IT exceed returns to other investments (Dedrick et al. 2003). Notwithstanding the relation between IT investment and productivity, evidence of IT's impact on financial measures of performance has until recently remained elusive.[3] For example, Hitt and Brynjolfsson (1996) find no relationship between IT capital investment and subsequent total shareholder return, return on assets (ROA), or return on equity (ROE). They suggested that IT's productivity benefits are competed away, creating consumer surplus rather than firm profits. Others argue that firm- and industry-specific factors help explain the wide variance in IT's impact on performance across firms (Bharadwaj 2000; Stratopoulos and Dehning 2000; Ross and Weill 2002; Bhatt and Grover 2005). The current study is the first to investigate systematically how these contextual factors influence IT budget levels as well as the relationship between IT budgets and financial performance.

Accounting research highlights the role of budgets in enabling senior managers to allocate resources to achieve performance targets (e.g., Kaplan and Norton 2001). Simons (1995) argues that firms use management control mechanisms such as budgets to achieve business performance objectives by stimulating and constraining opportunities. A firm's opportunity space is determined by its competitors, industry structure and history, customers, suppliers, innovation potential, existing asset and customer base, skills, and competencies. Consistent with that premise, budgeting research finds that budget allocations vary with an organization's environmental, organizational, and technological context (Covaleski et al. 2003). However, prior empirical budgeting research is primarily survey-based. That research focuses on attributes of the budgeting process, such as managerial participation, performance evaluation, budget importance, and use of operating budgets (Abernethy and Brownell 1999; Covaleski et al. 2003; Luft and Shields 2003), and does not describe how budget levels vary with context or how budget allocations subsequently impacted financial performance. Covaleski et al. (2003) suggest this may be due to a lack of data for analysis, as regulatory agencies such as the SEC and FASB do not require firms to disclose budget data.

Thus, IT budget data provide a unique opportunity to examine the determinants and consequences of firms' budget allocation decisions. Using firm-level IT budget data for the period 1991 to 1997, we find that a cross-sectional model explains substantial variance in IT budget levels. Thus, contingent environmental, organizational, and technological factors influence managers' budget allocations. We then use a second stage model to show that predicted IT budget levels are significantly positively related to future operating performance, indicating that the contextual factors, the resulting IT expenditures, or some combination of both affect performance. Furthermore, the idiosyncratic portions of IT budget levels (residual IT) also remain positively related to future financial performance after controlling for the direct effects of context, which suggests that context is not an explanation for this relationship between residual IT budget and performance.

This study contributes to both the management accounting and accounting information systems (AIS) literatures. It advances the managerial accounting literature by providing evidence based on actual budget data that contextual factors influence managers' budget decisions for IT, confirming a contingency theory view of IT budget formulation. Furthermore, we identify specific firm and industry factors that drive IT budgets, contributing to the AIS literature. In particular, we predict and confirm that IT budgets vary with the strategic role of IT within an industry, which provides further insight into a classic framework within the IS literature.

---

[2] See Chan (2000) and Dedrick et al. (2003) for reviews of the IT and productivity literature.

[3] See Dehning and Richardson (2002) and Melville et al. (2004) for reviews of the IT and firm performance literature.

This study further contributes to the AIS literature by linking IT budget levels and future firm profitability. With the exception of unpublished work by Anderson et al. (2003), this is the first study to make such a link. We provide new evidence that contextual factors substantially influence the relation between IT budget levels and firm performance. We show that these previously unexamined factors account for a significant portion of IT's apparent impact on performance, and controlling for those factors reduces but does not eliminate the positive marginal effect of IT on future performance. We also find evidence that stock market participants respond to IT budgets in a delayed fashion; firms with higher IT budget levels exhibit higher market returns over the subsequent three years. Prior AIS research employed event studies to analyze the relationship between announcements of IT investments and stock market performance (Dos Santos et al. 1993; Dehning et al. 2003; Oh et al. 2006). This study is the first to show a link between IT budget levels and subsequent market performance.

The remainder of the paper is organized as follows. Section II describes the development of our model of the determinants and consequences of IT budget levels and the corresponding expectations. Section III describes the data and research methodology. Section IV describes results. Section V discusses the limitations of this study. We summarize findings and conclude in Section VI.

II. MODEL AND THEORY DEVELOPMENT

Kaplan and Norton (2001) describe a process for managing strategy, the first step of which is to link the budgeting process to corporate strategy. Managers develop performance objectives and a strategy for obtaining these objectives (Porter 1985; Mintzberg 1988; Nyamori et al. 2001; Kaplan and Norton 2001), and then use budgets to establish specific performance targets and allocate resources to achieve these targets. The key challenge for managers is to align their resource allocation decisions with the firm's strategy and performance objectives.

The problem of matching investment decisions with strategy is explored in contingency research (Slagmulder 1996). It suggests that budgets should vary with environmental and organizational characteristics. Organizations are expected to adjust systematically their structure and practices (including budgets) to align contextual requirements arising from the environment with other less malleable organizational characteristics, including size and core production technology. Alignment occurs when a configuration of structure and process characteristics produces higher organizational performance than alternative configurations (Covaleski et al. 2003).

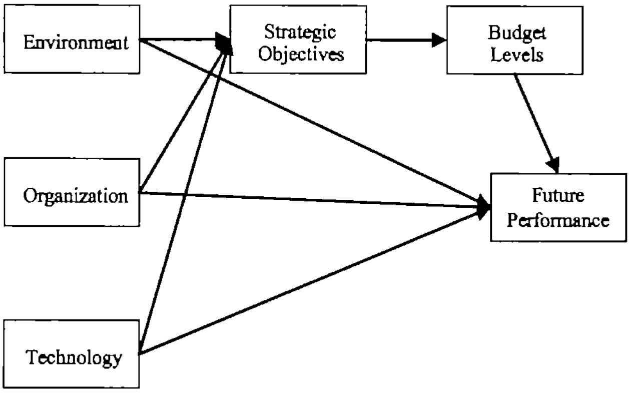
We therefore propose a theoretical model of the determinants and consequences of budgets as shown in Figure 1. In this model, environmental, organizational, and technological factors influence the organization's strategic objectives, which in turn influence budget levels. Subject to contextual needs and constraints and their associated competitive implications, managers set budget levels consistent with strategic objectives to improve future firm performance.

To apply this theoretical model for IT budgets, we propose the operational model shown in Figure 2 in which contextual factors that affect strategy and constrain firm performance also determine the IT budget level, which in turn influences future performance. Although firm capabilities and related contextual factors affect both IT budget levels and future firm performance, Figure 2 focuses on the incremental role of IT budgets. We explain the theory behind Figure 2 in the following sections. First, we describe specific environmental, organizational, and technological factors that should affect IT budget levels. Then, we characterize the relation between IT budget level and performance.

Environmental Factors and IT Budget Levels

Prior theoretical and empirical research addresses how three environmental factors—industry concentration, uncertainty, and product-market diversity—affect IT investment. Economic theory

FIGURE 1
General Model of IT Budget Determinants and Consequences



predicts that competition decreases as fewer firms dominate a market. Consistent with theory, Dewan and Mendelson (1998) find that the incentive to invest in IT is higher in markets with fewer competitors. The incentive for IT investment increases, since the benefits of IT are not competed away. *We therefore expect a positive relation between industry concentration and IT budget levels.*

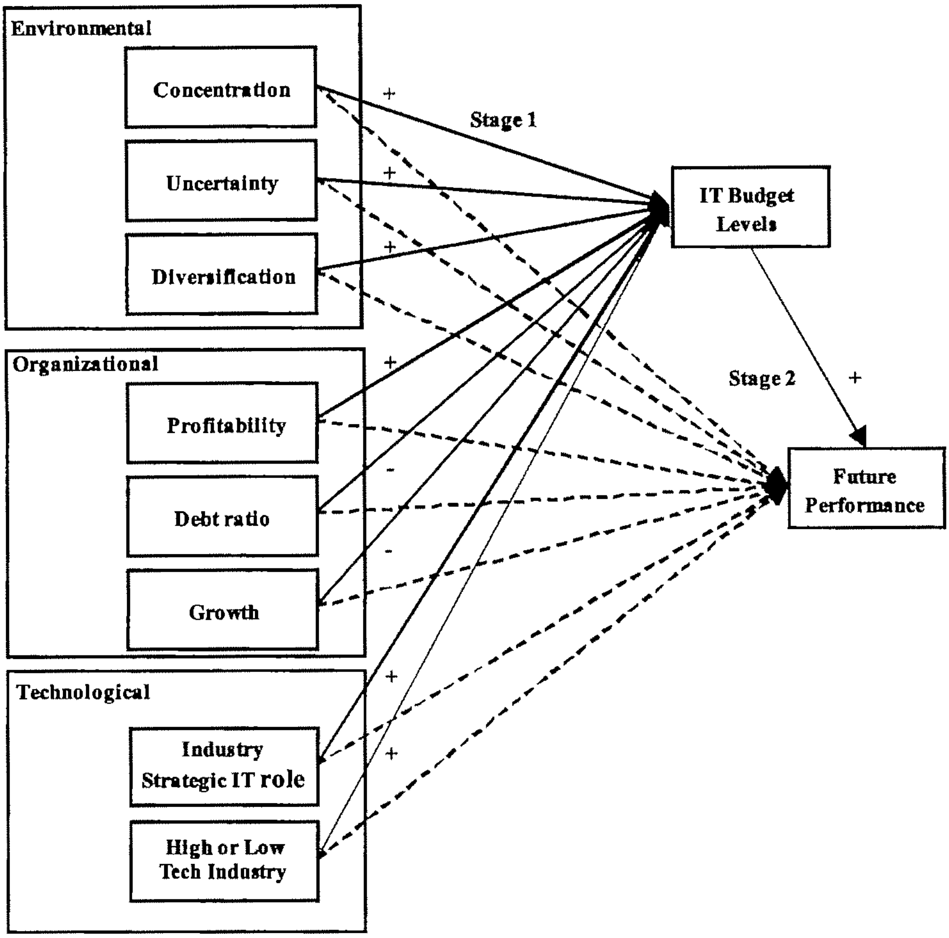
Organizational theory recognizes environmental factors as primary drivers of organizations' use of coordination and control mechanisms (Burns and Stalker 1961; Lawrence and Lorsch 1967; Thompson 1967; Pfeffer and Salancik 1978). More complex environments demand higher levels of coordination to achieve a given level of performance, since environmental complexity increases uncertainty (Galbraith 1977). That uncertainty affects the nature and variability of the tasks carried out by the firm (*cf.*, March and Simon's [1958] "task variability"). Thus, higher uncertainty should result in greater volatility in sales and income for a firm given its unique mix of product offerings and associated supply chain. Dewan and Mendelson (1998) link this to IT by relating the value of an information system to the frequency of information events that it captures. Similarly, Broadbent et al. (1996) find that marketplace volatility is correlated with the building of a more extensive IT infrastructure. Higher levels of uncertainty impose greater coordination demands, which in turn necessitate more sophisticated IT-enabled information processing. *We therefore expect a positive relation between uncertainty and IT budget levels.*

In a similar vein, the number of different product-markets in which the firm competes affects the incentive for IT investment. Lawrence and Lorsch (1967) find that firms operating in multiple markets will develop specialized functions. If each function serves a different market, there is less need to coordinate across functions to achieve overall firm performance objectives. Dewan et al. (1998) distinguish between related and unrelated product-market diversification[4] and find the former to be positively related to aggregate IT capital, providing empirical support for this theory within an IT setting. They find no relation between unrelated diversification and IT capital and attribute this to the lack of operational synergy between unrelated business segments. *We therefore*

---

[4] Related diversification is operating in product markets having different four-digit SICs but the same two-digit SIC. Unrelated diversification is operating in product markets having different two-digit SICs.

FIGURE 2
Operational Model of IT Budget Determinants and Consequences



expect a positive relation between related diversification and IT budget levels but no relation between unrelated diversification and IT budget levels.

Organizational Factors and IT Budget Levels

Many IT expenditures are regarded as discretionary, set based on what the business can afford after meeting other nondiscretionary costs and financial obligations. When budgets are squeezed, it is not uncommon for firms to delay, scale back, or cancel perceived non-critical IT-related activities. The inherent uncertainty regarding the payoffs to IT expenditures and the challenge of tracing IT expenditures to tangible performance outcomes also increase the difficulty of developing compelling business cases relative to alternative expenditures (Richardson and Zmud 2002). Consequently, the timing and magnitude of IT expenditures likely depend on the availability of internally generated funds, consistent with research on R&D and advertising expenditures (Kamien and Schwartz 1978; Perry and Grinaker 1994; Joseph and Richardson 2002). *We* *therefore expect a positive relation between operating profit and IT budget levels.* Since significant leverage and related debt service reduce the internally generated funds available for IT and other discretionary expenditures, *we also expect a negative relation between debt levels and IT budget levels.*

Dewan et al. (1998) find that firms with greater growth options invest less in IT. They suggest that growth imposes demands on cash flow; this, along with other high net present value projects, restricts amounts available for discretionary items such as dividends and IT budgets. Furthermore, installed IT assets often provide economies of scale with respect to the increases in transaction volume associated with sales growth. *We therefore expect a negative relation between sales growth and IT budget levels.*

Technological Factors and IT Budget Levels

Competitive dynamics, business processes, and the nature of the installed IT assets necessary to meet the resulting information processing requirements vary across industries. On the other hand, a similarity in these requirements portends considerable similarity in the nature and extent of IT use and, hence, a dominant strategic IT role within each industry (Dehning et al. 2003; Chatterjee et al. 2001).

Schein (1992) identified four strategic IT roles: (1) automate, replace human labor by automating business processes; (2) informate up, provide detailed information about business activities to senior management, and/or (3) informate down, provide collective information about business activities to employees across the firm; and (4) transform, apply IT in new ways fundamentally to redefine business processes and relationships. The IT strategic role construct has been incorporated into research models examining the business value of IT at the industry level (Anderson et al. 2006; Chatterjee et al. 2001; Dehning et al. 2003), the firm level (Armstrong and Sambamurthy 1999), and the IT investment initiative level (Dehning et al. 2003). Here, we apply the construct at the industry level.

Automate and transform roles both require robust technology platforms to enable core work processes. Firms in automate industries operate within relatively stable business domains with stable technology regimes and with competitive pressures recurrently to lower cost structures. In deploying their IT assets, automate firms typically build and then incrementally enhance robust technology platforms that host associated IT-enabled work processes. Conversely, firms in transform industries operate within less stable business domains and more dynamic technology regimes; therefore the transform IT role focuses on regularly "reinventing" a firm's technology platforms to induce dramatic shifts in IT-enabled work processes or to develop new product-market niches.

Informate industries are characterized by dynamic product-markets but relatively stable technology regimes. Firms in informate industries therefore tend to invest less in robust technology platforms, and instead focus on flexible work and decision processes. Informate firms typically require larger complementary investments in human (e.g., training) and structural capital (e.g., the redesign of work processes, decision structures and accountabilities, and reward structures) to move information more effectively up, down, or across organizational structures. However, these often substantial investments are typically accounted for in operating unit budgets rather than IT budgets.

We argue that IT-related complexities and corresponding costs increase when firms must build, maintain, and adapt robust technology platforms to compete effectively in their industry. *We therefore expect firms in industries where IT has an automate or transform strategic role to have higher IT budget levels than firms in industries where IT has an informate strategic role.*

The nature of business activity in an industry could also influence IT investment decisions. A number of researchers have documented the relation between IT investment and productivity (e.g., Brynjolfsson and Hitt 1996). Researchers and government officials attribute much of overall productivity growth to high-tech industries, where IT expenditures have generated large productivity gains (Oliner and Sichel 2000; Pakko 2002; Gordon 2003). *Thus, we expect higher IT budget levels in high-tech industries.* Relatively little is known, however, about the effect of IT in low-tech industries, so we make no prediction for those industries.

IT Budget Levels and Firm Performance

Although prior IS research establishes an empirical relation between IT investment and firm productivity, the link between IT investment and financial measures of firm performance has been elusive. Hitt and Brynjolfsson (1996) find no significant statistical relationship between IT investment (computer capital) and next-year total shareholder return, measured as ROA or ROE, for a sample of large firms over 1988–1992. They suggest that IT's benefits are competed away to become consumer surplus, as seen in the retail banking industry with ATMs. In this vein, Carr (2003) argues that the commoditization of IT reduces opportunities to create IT-based competitive advantage. Dehning and Richardson (2002) conclude that evidence of the link between IT investment and financial measures of firm performance is mixed.

Anderson et al. (2003) find that, notwithstanding the effects of competition, actual IT budget levels are positively related to both future ROA and ROS. Specifically, they find a statistically reliable association between IT budgets and future earnings, particularly where IT played an informate role (using IT to improve information flows throughout organizations). They also find a smaller but still significant association between IT budgets and future earnings where IT plays an automate role (using IT to facilitate automation of business processes). This offers evidence of a positive link between IT spending and financial performance.

These findings do not, however, address a central question of contingency budgeting research: Does budgeted spending that is consistent with contextual factors generate higher performance than budgeted spending that is not? To address this question, we distinguish between the context-driven component (predicted IT) and the firm-specific idiosyncratic component (residual IT). We propose the context-driven component as a proxy for aligned budgets and the idiosyncratic portion as a proxy for unaligned portions of the budgets. From a management control perspective, Kaplan and Norton (2004) argue that information capital creates value for a company when it is aligned with the company's strategy. Previous budgeting research using contingency theory indicates that environmental, organizational, and technological levels help determine the combination of organizational structure and processes that yields optimal performance levels (Drazin and Van de Ven 1985; Covaleski et al. 2003). Given that IT can have a significant impact on information capital, structure, and processes (Gurbaxani and Whang 1991), variations in context should lead to variations in the optimal, or aligned, level of IT budget. *Since the context-driven component of IT budgets should lead to the highest level of future performance, we expect that budget amounts that depart from this amount (i.e., spending more or less) will lead to lower levels of performance.*

III. DATA AND RESEARCH METHODS

We obtained IT budget data from *InformationWeek* magazine, a weekly print magazine aimed at business technology professionals. Since 1991 *InformationWeek* has conducted annual surveys to gather IT spending plans for the coming year from a variety of large public and private firms and government entities. In 1998, however, *InformationWeek* stopped publishing individual firm IT budget data in their public *InformationWeek* 500 reports. *InformationWeek* did continue publishing industry-level averages and more recent averages remain consistent with those reported in the 1991 to 1997 time frame.

The complete *InformationWeek* data set contains 2,186 firm-years IT budget-level observations for the period 1991 to 1997. We eliminated observations for non-public firms and matched the remaining data with corresponding Compustat financial data to calculate the various proxies for the environmental, organizational, and technological determinants of IT budget levels. This reduced the overall sample to 1,652 firm-year observations for 562 firms.[5]

Determinants of IT Budget Model

To examine the relation between contextual factors and IT budgets, we estimate the following cross-sectional regression model after scaling IT budgets by sales revenue:

$$\begin{aligned} IT\_sls_{it} = {} & \beta_0 + \beta_{E1} ind\_conc\_ratio_{it} + \beta_{E2} uncertainty_{it} + \beta_{E3} rel\_divers_{it} + \beta_{E4} unrel\_divers_{it} \\ & + \beta_{O1} op\_ros_{it} + \beta_{O2} debt\_ratio_{it} + \beta_{O3} sales\_growth_{it} + \beta_{T1} automate_{it} \\ & + \beta_{T2} transform_{it} + \beta_{T3} hi\_tech_{it} + \beta_{T4} lo\_tech_{it} + \varepsilon_{it} \qquad (1) \end{aligned}$$

where i indicates the firm, t indicates the year, the E, O, T coefficient subscripts indicate environmental, organizational, and technological factors respectively, *ind_conc_ratio* equals the four-firm industry concentration ratio at the four-digit SIC level, *uncertainty* equals the standard deviation of earnings (net income before extraordinary items) for the previous five years deflated by sales in year $t-1$, *rel_divers* and *unrel_divers* equal measures of related and unrelated diversification for the firm's reported business segments, respectively, *op_ros* equals operating income before depreciation divided by sales in year t, *debt_ratio* equals long-term debt divided by total assets, *sales_growth* equals the average sales growth (current year sales divided by previous year sales) for years t and $t-1$, *automate* and *transform* are dummy variables indicating the strategic role of the industry per *InformationWeek*, and *hi_tech* and *lo_tech* are dummy variables indicating that the industry (three-digit SIC) is high-tech or low-tech. Each variable is described further below.

While we recognize that prior IT budget levels are pragmatically used as a starting point in determining IT budget levels and, hence, will be related to these IT budget levels, we argue that managers justify IT budget levels on a basis of future costs and benefits rather than prior IT budget levels. Thus, we focus on the cross-sectional determinants of IT budget levels.

We measure industry concentration ratio (*ind_conc_ratio*) as the annual sum of sales revenue for the largest four firms in each four-digit SIC code divided by the sum of sales for all firms in that SIC code (e.g., Besanko et al. 2001; Zhao and Zou 2002). We expect industry concentration levels to be positively related to IT budget levels, since industries with higher concentration levels share the benefits of IT investment among fewer competitors.

We measure uncertainty (*uncertainty*) as the standard deviation of each firm's net income before extraordinary items for the previous five years (years $t-5$ to $t-1$), scaled by sales in the previous year (year $t-1$).[6] The standard deviation of earnings provides a general measure of risk (e.g., Kim 2001). We expect uncertainty to be positively related to IT budget levels, since greater environmental uncertainty should necessitate both greater coordination within the firm and with external partners and greater environmental monitoring efforts to mitigate the higher risk.

---

[5] *InformationWeek* estimated firm budgets for 153 observations based on firm revenue, IS employees, and prior IS budget if reported, and otherwise based on an estimate of revenue, IS budget and number of employees for firms in the same industry and then weighted by relative revenue. We ran the analysis and statistical tests with and without these *InformationWeek*-estimated figures and find qualitatively similar results between the two samples.

[6] We also tested alternate industry (three-digit SIC) level uncertainty measures, such as the standard deviation of sales for years $t-5$ to $t-1$ scaled by mean industry sales in year $t-1$, with qualitatively similar results.

We measure product-market diversification using reported business segment information from Compustat. Following Dewan et al. (1998), we employ entropy measures developed by Jacquemin and Berry (1979) to test the impact of product market diversification. Related diversification (*rel_divers*) is a sales-weighted measure of the extent to which firms operate across multiple four-digit SIC codes that are *within* a two-digit SIC code, and unrelated diversification (*unrel_divers*) similarly measures the extent of operations *across* two-digit SIC codes.[7] Based on Dewan et al. (1998), we expect related diversification to be positively related to IT budget levels, since firms with greater diversification should require higher levels of IT integration across related businesses, but we do not expect unrelated diversification to be related to IT budget levels, since firms are less likely to use IT to integrate across unrelated businesses.

We measure profitability (*op_ros*) as operating income before depreciation scaled by revenue.[8] This measure provides several advantages. It is not affected by changes in capital structure, interest payments, and other non-operating expenses, such as special items and income taxes, which should have little impact on IT budgets. We expect profitability to affect a firm's ability to invest in IT, so we expect a positive relation between operating profit and IT budget levels.

We measure leverage (*debt_ratio*) as the ratio of long-term debt to total assets. All else equal, higher debt and correspondingly higher interest payments constrain firms' abilities to invest in IT, so we expect a negative relation between debt levels and IT budget levels.

We measure growth (*sales_growth*) as mean percentage sales growth for the previous and current year (i.e., year $t - 1$ and t). We use the mean value for the previous two years to reduce the influence of temporary fluctuations in sales. Sustaining sales growth imposes cash flow demands, and IT assets provide economies of scale to support increased transaction volumes. Thus, firms with higher sales growth often under-invest in IT (Dewan et al. 1998). We therefore expect a negative relation between sales growth and IT budget levels.

We measure industry strategic IT role using dummy variables to identify the dominant strategic role of IT of an industry (using *InformationWeek* industry designations)[9] per Chatterjee et al. (2001). They sent an instrument detailing IT strategic role to four well-recognized scholars who both research and teach in the area of IT strategy and asked each judge to indicate whether IT served automate, informate (up or down), or transform role within an industry. The judges assessed strategic roles for both the pre-Internet period (1987–1994) and the post-Internet period (1995–1998). The inter-rater reliability was 0.80 for the period from 1987 to 1994 period and 0.82 for 1995 to 1998.[10] This measure of the industry strategic IT role construct has subsequently been used by others (e.g., Dehning et al. 2003; Anderson et al. 2006) in explaining industry differences in the value implications of IT investments.

---

[7] Related and unrelated diversifications are defined as follows. Let N be the number of four-digit SIC industries a firm is active in, indexed by i, which in turn aggregate into M two-digit industry groups, indexed by j. ($M \leq N$). N_j is the number of different industries in group j. s_i is share of industry i in total firm sales, s^j is share of group j in total firm sales, and s_i^j is the sales to each industry i divided by sales to the group j, calculated for each firm. Then, *rel_divers* is measured by $RD = \sum_{j=1}^{M} \sum_{i=1}^{N_j} s_i^j \ln \frac{s_j}{s_i^j}$, and *unrel_divers* is measured by $UD = \sum_{j=1}^{M} S^j \ln \frac{1}{s_j}$. See Dewan et al. (1998) or Jacquemin and Berry (1979) for further detail.

[8] We also estimated Equation (1) and the subsequent performance equations using free cash flow scaled by sales instead of operating profit. The results using free cash flow instead of operating profit are qualitatively similar, although only for the subset of firms that report cash flow measures.

[9] We also assigned these variables based on SIC codes with little difference in the results.

[10] For those few industries not explicitly covered by Chatterjee et al. (2001) and Dehning et al. (2003), two of the authors coded them in an attempt to match them to similar industries that were covered by these two studies. The authors then compared the coding and came to a consensus on the appropriate industry IT strategic role.

We further measure the nature of business activity as either high-tech or low-tech following the classification scheme in Francis and Schipper (1999) who use dummy variables that indicate whether the industry (three-digit SIC) is high-tech (*hi_tech*), low-tech (*lo_tech*), or not designated.[11] We expect firms in high-tech industries to have higher IT budget levels to maintain higher levels of innovation. Since relatively little is known about the effect of IT within low-tech industries and since Francis and Schipper's (1999) low-tech industry designations may not be complete, we make no specific prediction about IT budget levels in those industries.

We also test an alternative version of Equation (1) that includes lagged median industry IT-to-sales ratio for all other firms in the same two-digit SIC to control for omitted industry-level environmental and technological factors. Although this model explains greater variance in IT budget levels as expected, it does not identify the specific factors driving IT budget levels other than industry participation. The alternative model also produces similar results in the subsequent performance analyses, so we focus on the cross-sectional model specified in Equation (1).

Performance Consequences of the IT Budget Model

Figure 2 further indicates an expected relationship between IT budget levels and future firm performance. We assume that rational managers make resource allocation decisions that are expected to result in positive returns on investment. Since many of the benefits from IT investment are likely delayed, we examine performance over the three years (years $t+1$, $t+2$, and $t+3$) following the IT budget decision, controlling for performance in the IT budget year (year t) as well as other factors known to influence future performance.

To examine the relation between IT budget levels and future performance we use a two-step process. First, we separate each reported IT budget figure (scaled by sales) into two components: (1) a context-driven IT budget amount, and (2) an idiosyncratic residual IT budget amount. Using Equation (1) we determine the context-driven IT budget level (*predicted_IT*). We then calculate residual IT budget amounts as the actual budget minus the predicted budget, i.e., the extent to which managers have spent more or less than other firms in comparable contexts.

Second, to examine the relation between these two components of IT budget levels and future performance, we then estimate the following cross-sectional regression model:

$$Perf_{it+n} = \alpha_0 + \alpha_1 Perf_{it} + \alpha_2 cap\_intens_{it} + \alpha_3 rd\_sls_{it} + \alpha_4 adv\_sls_{it} + \alpha_5 size_{it} + \alpha_6 predicted\_IT_{it} + \alpha_7 residual\_IT_{it} + v_{it} \quad (2)$$

where i indicates the firm, t the year, and n future years 1, 2, or 3 or the average of all three.

Equation (2) includes other variables expected to influence future firm performance, including capital intensity (*cap_intens*), R&D expense scaled by sales (*rd_sls*), advertising expense scaled by sales (*adv_sls*), and size (*size*). We measure capital intensity as total assets divided by sales revenue, i.e., the inverse of asset turnover. Thus, higher capital intensity indicates lower ROA, all else equal (Francis et al. 2004; Cheng 2005). There is a large body of research that examines the contribution of both R&D and advertising expenditures to firm value, so we expect that both variables will be positively related to firm performance (e.g., Lev and Sougiannis 1996). We also control for size, measured as the natural log of sales, since size is often cited as affecting firm performance (e.g., Francis et al. 2004). In comparison, Anderson et al. (2003) employ controls for only current and lagged performance.

---

[11] Francis and Schipper (1999) focused on firms in high-tech industries and were not exhaustive in their coding of low-tech industries.

This equation also adds *predicted_IT*, the context-driven component of IT budgets, as a control variable. Because *predicted_IT* is a linear combination of Stage 1 contextual variables, some of which have been shown to be related to future firm performance in other circumstances (e.g., Piotroski 2000; Mohanram 2005), its coefficient reflects the extent to which these variables drive both IT and performance, and not the performance effects of aligned IT. To test the expectation that departures from the *predicted_IT* benchmark will lead to lower levels of performance, we examine the coefficient for idiosyncratic budget amounts (*residual_IT*: the firm's actual IT budget for that year minus *predicted_IT*).

We use two broad, standard measures of firm operating financial performance (*Perf*) in Equation (2): operating profit margin (*op_ros*) and operating return on assets (*op_roa*); *op_ros* equals operating earnings before depreciation divided by sales revenue, and *op_roa* equals operating earnings before depreciation divided by total assets. We adopt operating measures of performance because we expect IT to affect operations and not non-operating items included in net income (e.g., interest income and expense, taxes, discontinued operations, unusual write-offs and extraordinary items). We control for current performance because we expect current profitability to be related to future performance (e.g., Piotroski 2000; Mohanram 2005).

IV. RESULTS

Overview of Sample and Industry Analyses

Table 1, Panel A presents summary statistics for the 1,652 observations in the sample with both IT budget information over the period from 1991 to 1997 and related Compustat data required to estimate Equation (1) and 1,465 observations for the future performance variables required to estimate Equation (2). The *InformationWeek* survey process is weighted toward larger companies, and that is confirmed in Table 1: the mean (median) annual sales revenue is $8.5 billion ($8.4 billion), presented as natural logs for the *size* variable. The mean (median) IT budget is 2.2 percent (1.8 percent) of sales, and almost 88 percent of firms in the sample have IT budget levels of less than 4 percent of sales. On average, IT budget levels exceed both R&D and advertising spending, which indicates the relative importance of the IT spending decisions to firms in this sample.[12] Confirming that sales revenue provides an appropriate scaling variable, the ratio of IT-budget-to-sales is almost completely unrelated to size. Although not shown in the table, the median IT-budget-to-sales ratio for the smallest (largest) 20 percent of firms is 1.7 percent (1.8 percent).

Table 1, Panel B summarizes the number of available IT budget observations for the 562 sample firms. There are 63 firms with at least six years of IT budget data and 265 firms with two years or less. Mean IT budget levels are generally unrelated to the number of years for which data are available. Only the firms with three years of IT budget data have lower IT budget levels (1.90 percent versus 2.21 percent overall, significant at $p < 0.05$, one-tailed t-test with unequal variances).[13]

Table 1, Panel C summarizes actual IT budget levels, scaled by sales, for each year by industry type, defined by either strategic IT role or high- and low-tech. First, we compare mean IT budgets for automate, informate, and transform firms. Almost 55 percent of firms fall into the informate category, although informate firms have the lowest mean IT budget levels. About 15 percent of firms fall into the transform category, and as expected those firms have the highest

---

[12] During this period, IT spending on hardware and software grew from 16.6 percent to 19.5 percent of U.S. nonresidential private investment (Bureau of Economic Analysis 2007).

[13] Eliminating firms with only three IT budget observations from the sample did not change any inferences in subsequent analyses.

TABLE 1
Descriptive Statistics

Panel A: Summary Statistics (n = 1,652; all variables except *size, predicted IT,* and *residual IT* winsorized at 2 percent)

Variable	Mean	Median	Min.	Max.
it_sls (actual IT budget)	0.022	0.018	0.002	0.079
ind_conc_ratio	0.643	0.685	0.150	1.000
uncertainty	0.028	0.019	0.002	0.125
rel_divers	0.195	0.000	0.000	1.056
unrel_divers	0.329	0.021	0.000	1.287
op_ros	0.173	0.147	−0.036	0.434
debt_ratio	0.200	0.184	0.000	0.648
ave_sales_growth	1.071	1.061	0.802	1.479
ind_med_it_sls	0.021	0.018	0.002	0.123
rd_sls	0.017	0.000	0.000	0.130
adv_sls	0.009	0.000	0.000	0.110
size (ln sales)	8.516	8.417	4.764	12.037
F123op_ros[a]	0.179	0.154	0.010	0.434
F123op_roa[a]	0.138	0.136	0.008	0.309
cap_intens	2.203	1.014	0.252	12.729
Predicted IT	0.022	0.021	−0.002	0.051
Residual IT	0.000	−0.002	−0.046	0.067

Panel B: Description of Number of Observations per Firm and Mean IT Budget Levels[d]

# Years with Available *it_sls* Data	n[b]	# Firms	Mean it_sls
1	105	114	0.0199
2	277	151	0.0222
3	317	109	0.0190[c]
4	273	69	0.0223
5	280	56	0.0252
6	199	34	0.0245
7	201	29	0.0214
Total	1652	562	0.0221

(continued on next page)

TABLE 1 (continued)

Panel C: Mean IT Budget Amounts by Year and Industry Types

		Industry Type					
		Automate, Informate, or Transform			Low-Tech versus High-Tech		
Year	All	Automate	Informate	Transform	Low-Tech	Neither Low-nor High-Tech	High-Tech
1991	0.026	0.026^{e}	0.021	0.040^{e}	0.023	0.024	0.034^{g}
	178	110	56	12	25	122	31
1992	0.024	0.027^{e}	0.017	0.034	0.021	0.022	0.032^{g}
	205	137	64	4	26	145	34
1993	0.023	0.022	0.022	0.048	0.024	0.020	0.032^{g}
	187	117	68	2	26	130	31
1994	0.020	0.019^{e}	0.015	0.036^{f}	0.022	0.018	0.028^{g}
	189	39	111	39	25	133	31
1995	0.020	0.020^{e}	0.016	0.033^{f}	0.019	0.018	0.027^{g}
	353	62	216	75	49	247	57
1996	0.022	0.021	0.018	0.033^{f}	0.020	0.020	0.035^{g}
	363	55	231	77	51	263	49
1997	0.023	0.024	0.019	0.037^{f}	0.021	0.021	0.036^{g}
	177	36	109	32	22	133	22
Total	0.022	0.024^{e}	0.018	0.035^{f}	0.021	0.020	0.031^{g}
	1,652	556	855	241	224	1,173	255

Entries are *it_sls* (IT budget amounts scaled by sales) and number of observations; *it_sls* winsorized at 2 percent.

[a] n = 1,465.

[b] The number of observations is restricted to those with corresponding Compustat data necessary to test the determinants of IT budget levels in Table 3.

[c] The mean *it_sls* value is significantly smaller ($p < 0.05$, one-tailed t-test) for firms having three years of observations than for other firms; otherwise, there is no significant difference in mean *it_sls*.

[d] See Panel C for descriptive statistics for *automate*, *transform*, *hi_tech*, and *lo_tech*.

it_sls = IT budget amount divided by sales (Compustat data12);
size = log of sales (data12) in previous year;
op_ros = operating return on sales (data13/data12) in previous year;
uncertainty = standard deviation of earnings before extraordinary items for previous five years scaled by sales;
rel_divers = related diversification;
unrel_divers = unrelated diversification;
debt_ratio = debt ratio (data9/data6) in previous year;
ind_conc_ratio = four-firm industry concentration ratio (four-digit SIC);

(continued on next page)

TABLE 1 (continued)

sales_growth = average sales growth for $t-1$ and t;
med_ind_it_sls = median industry IT scaled by sales (two-digit SIC);
ave_sls_growth = sales (data12) in current year divided by previous year sales, average for years t and $t-1$;
cap_intens = capital intensity (data6/data12);
rd_sls = R&D exp. divided by sales (data46/data12);
adv_sls = advertising exp. divided by sales (data45/data12);
F123op_ros = mean operating return on sales (data13/data12) for years $t+1$, $t+2$, and $t+3$; and
F123op_roa = mean operating return on assets (data13/data6) for years $t+1$, $t+2$, and $t+3$.

Predicted IT and residual IT computed from Model (1) Table 3.

[e] Significantly higher than informate values ($p < 0.05$, one-tailed t-test with unequal variances).

[f] Significantly higher than informate values ($p < 0.01$, one-tailed t-test with unequal variances).

[g] Significantly higher than values for both low-tech and neither ($p < 0.01$, one-tailed t-test with unequal variances).

average IT budget levels. Budget levels for firms in the automate category are also significantly higher than for firms in the informate category, although those budget levels are substantially lower than for transform firms. For comparison, we also show average IT budget levels for high-tech, low-tech, and those firms not categorized as either high- or low-tech. As expected, high-tech firms have higher IT budget levels than other firms. High-tech firms' IT budget levels are similar to those for transform firms, and low-tech firms' budgets are similar to those of automate firms.

Table 2 presents correlations for various determinant and performance variables with Spearman correlations above the diagonal and Pearson correlations below the diagonal. As expected, IT budget levels (*it_sls*) are significantly positively related to operating profitability (*op_ros*), uncertainty, and the dummy variables indicating industry automate (*automate*) and transform (*transform*) strategic IT roles, as well as the dummy variable indicating high-tech industries (*hi_tech*). As also expected, IT budget levels are significantly negatively related to leverage (*debt_ratio*). Counter to expectations, IT budget levels are negatively related to industry concentration (*ind_conc_ratio*) and both diversity measures. However, after controlling for other factors affecting IT budgets in the regression analysis in Table 3, industry concentration is positively related to IT budget levels. Average sales growth (*ave_sls_gro*) is negatively related to IT budget levels, consistent with the argument that cash flow demands to support sales growth or the economies of scale related to IT assets dampens IT spending in higher growth firms.

Determinants of IT Budget Levels

We next examine the cross-sectional determinants of IT budget levels described in Figure 2. Table 1, Panel B shows that over half the firms in the sample have three or fewer IT budget observations per firm. These unbalanced panels restrict the use of panel estimation techniques, such as Prais-Winsten regressions or feasible generalized least squares that rely on estimates of sample serial correlation. Thus, we pool the sample and control for multiple observations from the same firms by adjusting standard errors for intragroup correlation (Froot 1989; Stata Press 2005). This approach presents conservative standard errors. In our tests of the subsample with at least three observations per firm, the clustered standard errors are over 30 percent larger than White's

TABLE 2
Correlations
(Spearman above the diagonal, Pearson below the diagonal, n = 1652)

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(1) *it_sls*	1	−0.15	0.29	−0.04	−0.21	−0.25	−0.11	0.11	0.26	0.26	−0.02	0.68	−0.10	0.34	0.38	0.13	0.02	0.01
(2) *ind_conc_ratio*	−0.15	1	−0.25	0.20	0.29	0.03	0.00	−0.16	−0.24	−0.01	−0.10	−0.21	0.25	−0.41	−0.48	0.31	0.14	0.04
(3) *uncertainty*	0.19	−0.23	1	−0.12	−0.12	−0.08	−0.18	0.12	0.15	0.11	0.08	0.28	−0.22	0.25	0.40	0.14	0.02	−0.11
(4) *rel_divers*	−0.05	0.20	−0.10	1	0.29	0.05	−0.04	−0.06	−0.14	−0.08	−0.13	−0.06	0.17	−0.01	−0.04	0.23	0.02	0.13
(5) *unrel_divers*	−0.21	0.29	−0.17	0.05	1	0.13	−0.05	−0.05	−0.16	−0.13	−0.01	−0.23	0.11	−0.13	−0.12	0.19	−0.02	0.11
(6) *debt_ratio*	−0.21	0.02	−0.03	−0.01	0.12	1	−0.13	0.06	−0.14	−0.12	0.13	−0.30	0.01	−0.08	−0.04	−0.14	0.03	0.06
(7) *ave_sls_gro*	−0.11	−0.01	−0.19	−0.04	−0.06	−0.11	1	−0.14	0.18	0.09	−0.07	0.00	0.17	0.09	−0.11	−0.03	0.00	0.06
(8) *automate*	0.07	−0.19	0.14	−0.06	−0.05	0.03	−0.12	1	−0.28	−0.02	0.15	0.09	−0.19	0.12	0.24	−0.07	−0.14	−0.02
(9) *transform*	0.31	−0.25	0.06	−0.13	−0.15	−0.13	0.18	−0.28	1	0.09	−0.05	0.37	−0.13	0.25	0.25	−0.22	−0.06	−0.04
(10) *hi_tech*	0.24	0.00	0.10	−0.06	−0.13	−0.12	0.09	−0.02	0.09	1	−0.17	0.29	0.27	0.15	−0.01	0.42	0.18	0.12
(11) *lo_tech*	−0.03	−0.11	0.08	−0.10	−0.02	0.14	−0.09	0.15	−0.05	−0.17	1	−0.04	−0.05	−0.23	−0.11	−0.07	−0.04	0.07
(12) *ind_med_it_sls*	0.63	−0.26	0.16	−0.05	−0.21	−0.20	0.00	0.05	0.43	0.25	−0.05	1	−0.16	0.37	0.43	0.07	−0.01	−0.08
(13) *op_roa*	−0.13	0.25	−0.22	0.16	0.10	0.03	0.13	−0.18	−0.13	0.27	−0.05	−0.19	1	0.18	−0.45	0.33	0.21	0.09
(14) *op_ros*	0.32	−0.49	0.13	−0.06	−0.18	−0.08	0.09	0.14	0.29	0.15	−0.21	0.41	0.11	1	0.71	−0.06	−0.04	0.00
(15) *cap_intens*	0.36	−0.51	0.22	−0.16	−0.26	−0.30	0.04	0.13	0.36	−0.14	−0.15	0.49	−0.56	0.55	1	−0.19	−0.17	−0.01
(16) *rd_sls*	0.14	0.12	0.16	0.14	−0.06	−0.23	0.03	−0.07	−0.10	0.57	−0.11	0.04	0.31	0.02	−0.22	1	0.18	0.09
(17) *adv_sls*	−0.06	0.13	−0.02	0.08	0.08	0.03	−0.02	−0.17	−0.07	0.10	−0.10	−0.06	0.20	−0.02	−0.15	0.16	1	0.18
(18) *size (ln sales)*	−0.01	0.05	−0.15	0.10	0.09	0.01	0.07	−0.04	−0.05	0.12	0.07	−0.06	0.09	−0.03	−0.12	0.09	0.16	1

corr > 0.04 significant at 10 percent, corr > 0.05 significant at 5 percent, corr > 0.06 significant at 1 percent.

it_sls = IT budget amount divided by sales (data12);
ind_conc_ratio = four-firm industry concentration ratio (four-digit SIC);

(continued on next page)

TABLE 2 (continued)

uncertainty = standard deviation of prior earnings before extraordinary items scaled by sales;
rel_divers = related diversification;
unrel_divers = unrelated diversification (see text for definition);
debt_ratio = debt ratio (data9/data6) in previous year;
ave_sales_gro = average sales growth for $t-1$ and t;
automate = 1 if automate industry IT role, 0 otherwise;
transform = 1 if transform industry IT role, 0 otherwise;
hi_tech = 1 if high-tech industry, 0 otherwise;
lo_tech = 1 if low-tech industry, 0 otherwise;
med_ind_it_sls = median industry IT scaled by sales (two-digit SIC);
op_roa = operating return on assets (Compustat data13/data6);
op_ros = operating return on sales (data13/data12);
cap_intens = capital intensity (Compustat data6/data12);
rd_sls = R&D expense divided by sales (Compustat data46/data12);
adv_sls = advertising expense divided by sales (Compustat data45/data12); and
size = natural log of sales (data12).

All variables except dummy variables (*automate, transform, hi_tech, lo_tech*) and *size* winsorized at 2 percent.

TABLE 3

Cross-Sectional Regression Analysis of Determinants of IT Budget Amounts

	Expected Sign	**(1)** it_sls_{it}	**(2)** it_sls_{it}
$ind\_conc\_ratio_{it}$	+	0.007 (2.33)**	0.007 (2.63)***
$uncertainty_{it}$	+	0.049 (2.22)**	0.041 (2.05)**
rel_divers_{it}	+	0.000 (0.30)	0.000 (0.11)
$unrel\_divers_{it}$	n.s.	−0.005 (3.77)***	−0.004 (2.99)***
op_ros_{it}	+	0.038 (5.32)***	0.022 (3.16)***
$debt\_ratio_{it}$	−	−0.019 (4.79)***	−0.013 (2.99)***
$ave\_sales\_growth_{it}$	−	−0.027 (6.13)***	−0.022 (5.37)***
$automate_{i}$	+	0.003 (3.00)***	0.002 (1.97)**
$transform_{i}$	+	0.013 (6.98)***	0.007 (3.59)***
hi_tech_{i}	+	0.008 (3.97)***	0.005 (3.11)***
lo_tech_{i}	?	0.003 (1.52)	0.003 (1.39)
$med\_ind\_it\_sls_{i,t-1}$			0.536 (6.36)***
Constant		0.039 (7.19)***	0.027 (5.21)***
Observations		1652	1430
Adj. R^2		0.28	0.38

*,**,*** Significant at 10 percent, 5 percent, and 1 percent, respectively. Robust t-statistics in parentheses (adjusted for intragroup correlation).

it_sls = IT budget divided by sales (Compustat data12);
ind_conc_ratio = four-firm concentration ratio for four-digit SIC;
uncertainty = standard deviation of earnings before extraordinary items for previous five years scaled by sales;
rel_divers = related diversification (within two-digit SICs);
unrel_divers = unrelated diversification (across two-digit SICs);
op_ros = operating return on sales (before depreciation) (Compustat data13/data12) at t;
debt_ratio = debt ratio (data9/data6) at t;
ave_sales_growth = average sales growth for $t-1$ and t;
automate = 1 for firms in automate industries, 0 otherwise;
transform = 1 for firms in transform industries, 0 otherwise;
hi_tech = 1 if high-tech firm, 0 otherwise;
lo_tech = 1 if low-tech firm, 0 otherwise; and
med_ind_it_sls = median *it_sls* for two-digit SIC at $t-1$.

All variables except dummy variables (*automate, transform, hi_tech, lo_tech*) winsorized at 2 percent.

(robust) standard errors and 157 percent larger than those obtained from feasible GLS. It also presents unbiased coefficient estimates, since OLS is unbiased even in the presence of serial correlation and heteroscedasticity (e.g., Wooldridge 2003).[14]

Table 3 presents results of cross-sectional regressions based on Equation (1). Column (1) presents results for the model specified in Equation (1). As an alternative specification to control for any omitted environmental factors, Column (2) further includes lagged median industry IT budget levels.[15] Although including median industry IT budget levels improves the model fit, it does not change the qualitative interpretation of the relation between the continuous variables, or the *automate* and *hi_tech* dummy variables, and firm IT budget levels. We therefore focus on the results in Column (1) as a direct test of the cross-sectional determinants of IT budget levels.

We use industry concentration, uncertainty, and diversification measures to test the effect of environmental complexity on firm IT budget levels. Table 3 shows that industry concentration (*ind_conc_ratio*) is significantly positively related to firm IT budget levels. These results are consistent with prior research, which argues that higher industry concentration increases the incentive for IT investment (Dewan and Mendelson 1998). Similarly, uncertainty is also positively related to firm IT budget levels, consistent with the argument that higher levels of uncertainty necessitate more sophisticated IT-enabled processing capabilities.[16] While the results for the two diversification measures differ from our expectations and Dewan et al.'s (1998) findings, they are consistent with the logic used to develop our expected relationships. Here, firms that diversify into unrelated markets have lower IT budgets, as expected since there is less benefit obtained from using IT to coordinate across unrelated businesses than to coordinate within a business unit or across related business units. Thus, it is important to distinguish between related and unrelated diversification in estimating their impact on budgets. In summary, the results shown in Table 3 indicate that environmental complexity influences IT budget levels.

We use operating profit, leverage, and growth measures to test the effect of organizational factors on firm IT budget levels. Table 3 shows that operating profit (*op_ros*) is significantly related to IT budget levels. Leverage (*debt_ratio*) is significantly negatively related to IT budget levels. Sales growth (*ave_sales_growth*) is also negatively related to IT budget levels. These results are consistent with the affordability argument; firms with higher operating profit, lower leverage, and fewer high net present value investment alternatives have greater resources available to invest in IT. With respect to the impact of organizational factors on IT budget levels, these results suggest that IT budgets increase with firms' ability to invest in IT.

We use two industry indicators, industry strategic IT role and industry technology intensity, to test the effect of technological factors on firm IT budget levels. Table 3 Column (1) shows that firms in *automate* or *transform* industries are characterized by higher IT budgets than *informate* firms. The coefficient for the *transform* variable is significantly greater than that for the *automate* variable ($p < 0.001$, analysis not shown). This is the first empirical confirmation that industries using IT to automate or transform are characterized by significantly higher IT budgets than those that invest primarily for informational purposes (the *informate* strategic IT role). The *hi_tech* firms also have higher IT budgets than other firms as expected. Furthermore, these firms have significantly higher budgets than the low-tech firms ($p < 0.001$, not shown). Thus, industry-level technological factors affect IT budget levels. Although there is some overlap of the two types of industries, the Spearman correlation is only 0.09 between *hi_tech* and *transform*, and 0.15 between *lo_tech* and *automate* (Table 2), indicating they are distinct.

---

[14] As a sensitivity test, not shown, we also estimated the models with bootstrapped standard errors with qualitatively similar results (e.g., Goncalves and White 2005; Efron and Tibshirani 1993). Goncalves and White 2005 show that bootstrapped standard error estimates are accurate in the presence of serial correlation and heteroscedasticity.

[15] We also estimated Equation (1) with a lagged dependent variable as an alternate test (not presented). This approach is often used to control for unknown but potentially correlated omitted variables (Wooldridge 2003). As is often the case, using the lagged dependent variable improves the model fit, but that variable dominates many of the other, relatively fixed variables in the model, such as the industry type dummy variables (see Achen [2000] for a discussion of the issues surrounding the use of lagged dependent variables).

[16] As a sensitivity test, the analysis was done using the standard deviation of three-digit SIC industry sales in the prior five years, scaled by mean industry sales in the prior year, as an alternate uncertainty measure to reduce firm-specific uncertainty. Results were qualitatively similar.

In summary, we find evidence that environmental complexity, resource availability, sales growth, and technological factors influence firm IT budget levels. As expected per Figure 2, IT budget levels are positively influenced by environmental uncertainty and industry concentration. Firms with greater related diversification have higher budget levels than firms with greater unrelated diversification. More profitable firms have higher IT budget levels, while firms with greater debt or higher growth have lower budget levels. Furthermore, IT budget levels vary with industry strategic IT role and the high-tech or low-tech nature of the industry. These results are generally robust to alternative specifications and across time.[17]

IT Budget Levels and Future Financial Performance

To examine the relation between the IT budget levels and future performance, we separate the IT budget level into two parts: (1) context-driven IT budget amounts (based on Equation (1)), and (2) residual IT budget amounts (actual minus context-driven budget). We then use these values to estimate the cross-sectional regression model specified in Equation (2).[18]

Table 4 presents results for estimates of Equation (2) relating IT budget levels to average performance in the three years after the budget year, controlling for current (year *t*) performance and other variables expected to influence future performance, including capital intensity (*cap_intens*), R&D expense (*rd_sls*), advertising expense (*adv_sls*), and *size*.

In columns (1) through (3) of Table 4, we present results for future *op_ros* (operating profit margin). Column (1) includes the IT budget separated into predicted and residual amounts. The *predicted_IT* coefficient reflects the extent to which contextual (i.e., Stage 1) factors drive both IT and performance, while the *residual_IT* coefficient reflects the marginal effect of departures from the *predicted_IT* budget. Both *predicted_IT* and *residual_IT* are positively related to *op_ros*. Separation of *residual_IT* into positive and negative values (i.e., spending above and below the *predicted_IT* benchmark) yields coefficients that are not significantly different (not shown).

The coefficient on *residual_IT* is significantly lower than the coefficient on *predicted_IT* ($p < 0.03$; analysis not shown).[19] Thus, the two IT budget components affect performance differently, which suggests that estimates of the effect of IT budget on future performance that do not control for the contextual determinants examined earlier may be significantly inflated.

Column (2) includes the actual IT budget amount (*it_sls*) for comparison because prior IT business value research has focused on actual IT amounts. Actual IT budget amount is significantly positively related to future operating profit margins; however, the coefficient on actual IT (0.234) in Column (2) is substantially higher than the *residual_IT* coefficient (0.163) in Column

---

[17] We also estimated the determinants of IT budget levels for each year in the sample (1991 to 1997). The results are similar to those presented for the combined sample shown in Table 3, although there are some differences across years. To test whether one year drives the overall results, we performed seven regressions sequentially holding out each year (1991 to 1997). In all cases, the results were substantially similar to those shown in Column (1) in Table 3. We therefore believe that no single year is driving the overall results.

[18] This is similar to a simultaneous equations process where the predicted value from the stage 1 model is used as a regressor for the stage 2 model. This yielded similar results when done using three-stage least-squares with bootstrapped standard errors (not shown for brevity), but did not allow us to consider the predicted and residual values separately.

[19] Separate analysis of performance in each future year ($t+1$ to $t+3$) yields similar results.

TABLE 4
Relation of Predicted, Residual, and Actual IT Budget Amounts (Scaled by Sales) to Future Operating Return on Sales and Return on Assets

	(1) $F123op\_ros_{it}$	(2) $F123op\_ros_{it}$	(3) $F123op\_ros_{it}$	(4) $F123op\_roa_{it}$	(5) $F123op\_roa_{it}$	(6) $F123op\_roa_{it}$
op_ros_{it}	0.859	0.872	0.849			
	(42.11)***	(44.83)***	(37.77)***			
op_roa_{it}				0.751	0.771	0.773
				(32.13)***	(33.28)***	(28.48)***
cap_intens_{it}	0.004	0.004	0.003	−0.004	−0.003	−0.003
	(4.38)***	(4.57)***	(4.11)***	(10.28)***	(9.05)***	(5.87)***
rd_sls_{it}	0.020	0.047	0.034	−0.009	0.035	0.029
	(0.40)	(0.94)	(0.62)	(0.16)	(0.63)	(0.44)
adv_sls_{it}	0.140	0.134	0.163	0.176	0.162	0.170
	(3.90)***	(3.81)***	(3.90)***	(2.94)***	(2.73)***	(2.71)***
$size_{it}$	−0.001	−0.001	−0.001	0.000	0.000	0.000
	(0.61)	(0.73)	(1.00)	(0.24)	(0.08)	(0.06)
predicted IT_{it}	0.580			0.788		
	(3.33)***			(5.53)***		
residual IT_{it}	0.163		0.189	0.133		0.121
	(2.09)**		(2.41)**	(1.84)*		(1.65)*
actual IT $budget_{it}$		0.234			0.257	
		(3.27)***			(3.93)***	
ind_conc_ratio			−0.017			0.002
			(2.92)***			(0.41)
uncertainty			−0.004			−0.076

(continued on next page)

TABLE 4 (continued)

	(1) *$F123op\_ros_{it}$*	(2) *$F123op\_ros_{it}$*	(3) *$F123op\_ros_{it}$*	(4) *$F123op\_roa_{it}$*	(5) *$F123op\_roa_{it}$*	(6) *$F123op\_roa_{it}$*
			(0.07)			(1.38)
related_divers			0.008			0.002
			(2.83)***			(0.63)
unrelated_divers			0.009			−0.004
			(3.42)***			(1.66)*
$debt\_ratio_{it}$			−0.010			−0.001
			(1.06)			(0.15)
$ave\_sales\_growth_{it}$			−0.015			−0.034
			(1.19)			(3.63)***
automate			0.009			0.004
			(4.03)***			(1.87)*
transform			0.012			0.016
			(3.28)***			(4.45)***
hi_tech			0.005			0.008
			(1.38)			(1.72)*
lo_tech			−0.001			0.001
			(0.23)			(0.22)
Constant	0.017	0.022	0.050	0.023	0.031	0.070
	(1.46)	(2.02)**	(2.47)**	(2.24)**	(3.05)***	(4.19)***
Observations	1465	1465	1465	1465	1465	1465
Adj. R^2	0.89	0.89	0.89	0.79	0.78	0.79

(continued on next page)

TABLE 4 (continued)

---

*,**,*** Significant at 10 percent, 5 percent, and 1 percent, respectively. Robust t-statistics in parentheses (adjusted for intragroup correlation).

i = firm;
t = time in years;
F123op_ros = mean operating return on sales (before depreciation) (Compustat data13/data12) at $t+1$ to $t+3$;
F123op_roa = mean operating return on assets (before depreciation) (Compustat data13/data6) at $t+1$ to $t+3$;
cap_intens = capital intensity (data6/data12) at *t*;
rd_sls = R&D expense divided by sales (data46/data12) at *t*;
adv_sls = advertising expense divided by sales (data45/data12) at *t*;
size = log of sales (data12) at *t*;
predicted_IT = predicted values from Model (1) Table 3;
residual IT = actual IT budget minus predicted IT;
actual IT b = IT budgets (scaled by sales) as reported by firm *i* in year *t* (i.e., *it_sls*);
ind_conc_ratio = four-firm concentration ratio for four-digit SIC;
uncertainty = standard deviation of earnings before extraordinary items for previous five years scaled by sales;
rel_divers = related diversification;
unrel_divers = unrelated diversification;
debt_ratio = debt ratio (data9/data6) at *t*;
ave_sales_growth = average sales growth for $t-1$ and *t*;
automate = 1 for firms in automate industries, 0 otherwise;
transform = 1 for firms in transform industries, 0 otherwise;
hi_tech = 1 if high-tech firm, 0 otherwise; and
lo_tech = 1 if low-tech firm, 0 otherwise.

All variables except size and dummy variables winsorized at 2 percent.

(1). Thus, 30 percent[20] of the estimate of IT returns based on actual IT spending is due to contextual factors. An increase in IT budget from 2 percent to 3 percent of sales will, on average, increase operating income by 0.16 percent of sales. To test if the direct effects of contextual variables affect IT budgets' relation to performance, Column (3) replaces *predicted_IT* with its predictors from the Stage 1 regression (Equation (1)). The *residual_IT* variable remains significantly positively related to future performance.[21]

Columns (4) through (6) present similar results for the relation between IT budget values and future *op_roa* (operating return on assets). Not surprisingly, capital intensive (*cap_intens*) firms have lower future *op_roa*, but higher future *op_ros*. Otherwise, the relation between control variables and future performance is generally similar. As expected, current operating performance is strongly related to future operating performance (*op_roa*). Again, the *residual_IT* coefficient is significant. Separate untabulated analysis also shows no difference between coefficients for positive and negative residuals; *residual_IT* is also lower than the *predicted_IT* coefficient in every model ($p < 0.001$, not shown) and lower than the coefficient for *actual IT* budget (0.257) in Column (5), again indicating that a substantial portion of estimates of IT returns is explained by contextual factors.

The evidence indicates that IT budget level is a positive predictor of future profitability. The positive *residual_IT* coefficient indicates that there are returns to incremental IT spending after controlling for contextual factors omitted in prior research. Furthermore, the substantial difference in the *residual_IT* and *predicted_IT* coefficients suggests that estimates of the performance impact based on *actual IT* amounts—the norm in prior research—may be overstated.

IT Budget Levels and Market Performance

As a further test of the relation between IT budget levels and firm performance, we examine the relation between IT budget levels and market performance for the three years after the budget was formed. Prior research suggests that the market values IT investments at a significant multiple (e.g., Bharadwaj et al.'s [1999] finding of a positive impact on Tobin's q), but no research has yet examined the long-term impact of IT budgets on future market returns.

In an efficient market, the stock price immediately impounds the value of a firm's IT expenditures, so current period IT budgets should not affect future period stock returns. However, the inherent uncertainty often associated with the costs and ultimate benefits of IT initiatives may confound this relationship (Dewan et al. 2007; Kobelsky et al. 2006). Thus, it is possible that the market response is delayed until the uncertainty associated with that firm's IT initiatives has largely been resolved (Richardson and Zmud 2002).

In addition, current accounting standards require that firms immediately expense most IT expenditures, which reduces current-period net income and thereby affects traditional stock valuation metrics such as price-earnings and market-to-book ratios, as well as key components of debt covenants and cost-of-capital calculations (Chan et al. 2001). As a result, stock prices may not fully incorporate the value of IT expenditures (Richardson and Zmud 2002).

To address the question of subsequent returns to IT budgets and to control for firm-specific IT risk, we formed sets of five portfolios based on predicted, residual, and actual IT budget levels (scaled by sales revenue) and sorted from lowest to highest. Thus, for each set portfolio 1 represents the 20 percent of firms with the lowest IT levels each calendar year, and portfolio 5 represents the 20 percent of firms with the highest IT levels each calendar year.

---

[20] $((0.234 - 0.163) / 0.234) = 30.3$ percent

[21] Using *actual IT*/sales rather than *residual_IT*/sales yields an IT variable coefficient that is identical for future *op_ros* and substantially similar (0.124 versus 0.121) for future *op_roa*.

Table 5 presents mean monthly market-adjusted returns for the budget year (t) and the three subsequent calendar years ($t+1$, $t+2$, and $t+3$). For each set of portfolios, the returns for portfolio 5 are significantly higher than returns for portfolio 1 in each year. Generally, the returns increase across the portfolios, with lower IT budgets associated with lower average monthly returns in all three years. Thus, higher IT budget levels indicate higher prospects for future market returns, but consistent with results in Table 4, the change across residual IT portfolios is less than the corresponding change in returns for both predicted and actual IT portfolios.

It is possible that the subsequent stock returns accruing to firms with higher IT budgets are due to systematic differences in risk among the firms making such IT investments. We therefore examine whether differences in returns for each of the three sets of portfolios persist after controlling for risk with Fama/French factor model regressions (Fama and French 1996; Chan et al. 1998). For each set of portfolios, we estimate the following model for monthly returns for each of the three years following the budget year:

$$R_{it} - R_{ft} = \mathrm{a} + \mathrm{b}_1[R_{mt} - R_{ft}] + \mathrm{b}_2 SMB_t + \mathrm{b}_3 HML_t + \mathrm{b}_4 UMD_t + \mathrm{e}_{it}, \tag{3}$$

where $R_{it} - R_{ft}$ is the monthly firm return minus the risk free rate, $R_{mt} - R_{ft}$ is the corresponding monthly value-weighted market return minus the risk free rate, *SMB* are returns on factor-mimicking portfolios based on size, and *HML* are the corresponding returns for portfolios based on book-to-market. The variable *UMD* controls for momentum with the difference in returns for market winners and losers over the six months ending one month before the current month (Chan et al. 1998). The value for a, the coefficient for the regression constant, then represents the excess return for the portfolio after controlling for the firms' risk exposure.

Panel A of Table 6 first presents Fama/French regression results for portfolios based on predicted IT budget values scaled by sales.[22] The constant coefficient, *a*, for portfolio 5 is significantly greater than zero ($p < 0.01$) and also nominally higher than shown for portfolio 1 in each future year, indicating that differences in returns across portfolios are partly due to contextual factors that covary with IT. Panel B next presents the results of Fama/French factor model regressions results for five portfolios based on actual IT budget values scaled by sales. Firms in portfolio 5 exhibit significantly positive risk-adjusted future returns across all three future years. Overall, portfolio 5 firms enjoy 0.4 to 0.9 percent higher monthly returns than firms in portfolio 1.

Table 6, Panel C finally presents similar analysis for idiosyncratic IT budget levels (residual IT). The results indicate significantly positive risk-adjusted future returns for portfolio 5. Thus, even after adjusting for contextual factors that drive both IT budgets and performance, shareholders in firms with the highest quintile IT budgets (portfolio 5) enjoy future monthly returns that are 0.3 to 0.7 percent higher than firms in the lowest quintile (portfolio 1), consistent with the strong relation between IT budget levels and firm financial performance shown in Table 4. The relation between IT budget levels and returns also increases over time; risk-adjusted excess returns for portfolio 5 increase across the three years after portfolio formation.

Assuming that we have adequately controlled for risk, it appears that capital markets are not efficient in their reactions to IT budget plans. Since large sample IT budget data are not generally available to the public, it may be that investors are unable to value IT's benefits until they are realized in earnings. Another complementary explanation is that even if investors have IT budget information they delay their response until the firm-specific uncertainties associated with IT's benefits are reduced (Richardson and Zmud 2002).

---

[22] Data for Fama/French benchmark portfolios are available on Kenneth French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

TABLE 5

Mean Monthly Return in Excess of Market Return for Portfolios Based on Annual IT/Sales Ratios Levels from Lowest (Portfolio 1) to Highest (Portfolio 5)

	Mean Monthly Excess Returns											
	Portfolios Based on Predicted IT/Sales[a]				Portfolios Based on Residual IT/Sales				Portfolios based on Actual IT/Sales			
Portfolio	Year t	Year $t+1$	Year $t+2$	Year$t+3$	Year t	Year $t+1$	Year $t+2$	Year $t+3$	Year t	Year $t+1$	Year $t+2$	Year $t+3$
1	−0.0019	−0.0041	−0.0072	−0.0064	−0.0011	0.0004	−0.0009	−0.0039	−0.0031	−0.0039	−0.0084	−0.0058
2	−0.0032	−0.0025	−0.0059	−0.0075	0.0018	0.0003	−0.0057	−0.0026	−0.0012	−0.0018	−0.0019	−0.0083
3	0.0003	−0.0002	−0.0054	−0.0041	−0.0004	−0.0018	−0.0051	−0.0037	0.0001	−0.0008	−0.0067	−0.0048
4	0.0021	0.0004	−0.0008	−0.0005	0.0022	0.0000	−0.0040	−0.0067	0.0033	0.0047	0.0004	0.0021
5	0.0073	0.0085	0.0069	0.0043	0.0020	0.0033	0.0030	0.0023	0.0055	0.0054	0.0053	0.0028
Total	0.0009	0.0004	−0.0026	−0.003	0.0009	0.0004	−0.0026	−0.0030	0.0009	0.0007	−0.0024	−0.0029
	Comparing Mean Excess Returns of Portfolio 5 to Portfolio 1											
Diff (5 − 1)	0.0092	0.0126	0.0141	0.0107	0.0012	0.0022	0.0025	0.0008	0.0086	0.0093	0.0138	0.0086
p(Diff = 0)	<0.001	<0.001	<0.001	<0.001	<0.01	<0.145	<0.10	<0.01	<0.001	<0.001	<0.001	<0.001

---

p(Diff = 0) based on two-tailed t-test of monthly excess returns for portfolio 5 minus portfolio 1; market return is value-weighted return.

[a] Predicted and residual IT/Sales values based on contextual model (Model 1, Table 3).

TABLE 6

Analysis of Relation between IT Budget Portfolios and Future Risk-Adjusted Market Returns

Panel A: Factor Model Regressions for Mean Monthly Risk-Adjusted Return in Excess of Market for Portfolios Formed Based on Predicted IT/Sales Levels from Lowest (Portfolio 1) to Highest (Portfolio 5)[a]

$R_{it} - R_{ft} = a + b_1[R_{mt} - R_{ft}] + b_2 SMB_t + b_3 HML_t + b_4 UMD_t + e_{it}$.

Portfolio	a	t(a)	b1	t(b1)	b2	t(b2)	b3	t(b3)	b4	t(b4)	n	Adj. R^2
One year after portfolios formed												
1	−0.001	(0.41)	0.895	(16.89)***	0.232	(3.73)***	0.214	(2.76)***	−0.200	(2.79)***	3424	0.12
2	−0.000	(0.32)	1.020	(21.97)***	0.080	(1.59)	0.298	(4.51)***	−0.363	(6.24)***	3544	0.17
3	0.001	(0.56)	0.981	(21.89)***	0.091	(1.79)*	0.364	(6.32)***	−0.258	(4.59)***	3577	0.16
4	0.000	(0.05)	1.056	(20.20)***	0.119	(2.19)**	0.283	(4.44)***	−0.189	(3.21)***	3387	0.15
5	0.005	(2.79)***	1.238	(23.99)***	−0.014	(0.24)	0.230	(3.12)***	−0.001	(0.02)	3431	0.21
Two years after portfolios formed												
1	−0.001	(0.47)	0.978	(19.70)***	0.233	(3.92)***	0.385	(4.73)***	−0.340	(5.94)***	3236	0.15
2	−0.001	(0.49)	1.049	(24.27)***	0.197	(3.50)***	0.485	(6.85)***	−0.338	(6.68)***	3481	0.19
3	−0.001	(0.64)	0.989	(21.78)***	0.051	(0.93)	0.350	(5.05)***	−0.311	(5.81)***	3507	0.17
4	0.002	(1.27)	0.970	(19.07)***	0.170	(2.75)***	0.329	(5.00)***	−0.190	(3.22)***	3314	0.15
5	0.007	(3.87)***	1.104	(22.89)***	0.036	(0.51)	0.148	(1.89)*	−0.062	(1.03)	3195	0.21
Three years after portfolios formed												
1	0.002	(0.71)	1.134	(19.82)***	0.343	(5.54)***	0.761	(7.23)***	−0.439	(7.24)***	2958	0.17
2	0.000	(0.11)	1.028	(21.59)***	0.212	(4.09)***	0.594	(7.45)***	−0.379	(7.40)***	3367	0.17
3	0.001	(0.80)	1.029	(21.60)***	0.095	(1.76)*	0.523	(6.61)***	−0.355	(6.81)***	3355	0.18
4	0.003	(1.54)	1.121	(21.05)***	0.227	(3.66)***	0.568	(6.38)***	−0.245	(4.15)***	3190	0.17
5	0.007	(3.48)***	1.061	(19.13)***	−0.059	(0.87)	0.085	(0.86)	−0.238	(3.93)***	2945	0.18

(continued on next page)

TABLE 6 (continued)

Panel B: Factor Model Regressions for Mean Monthly Risk-Adjusted Return in Excess of Market for Portfolios Formed Based on Actual IT/Sales Levels from Lowest (Portfolio 1) to Highest (Portfolio 5)^b

$R_{it} - R_{ft} = a + b_1[R_{mt} - R_{ft}] + b_2 SMB_t + b_3 HML_t + b_4 UMD_t + e_{it}$.

Portfolio	a	t(a)	b1	t(b1)	b2	t(b2)	b3	t(b3)	b4	t(b4)	n	Adj. R^2
One year after portfolios formed												
1	−0.001	(0.77)	0.956	(19.31)***	0.182	(3.29)***	0.224	(3.45)***	−0.252	(4.04)***	3558	0.13
2	0.000	(0.04)	1.000	(20.38)***	0.099	(1.80)*	0.275	(3.99)***	−0.312	(4.46)***	3618	0.15
3	−0.000	(0.30)	1.010	(23.01)***	0.057	(1.16)	0.326	(4.91)***	−0.190	(3.51)***	3606	0.17
4	0.004	(2.21)**	1.167	(23.36)***	0.107	(1.92)*	0.318	(4.91)***	−0.241	(4.09)***	3529	0.19
5	0.003	(1.94)*	1.094	(20.50)***	0.062	(1.08)	0.273	(4.05)***	−0.011	(0.19)	3476	0.16
Two years after portfolios formed												
1	−0.003	(1.78)*	0.936	(18.80)***	0.118	(2.10)**	0.396	(5.12)***	−0.373	(6.68)***	3449	0.13
2	0.002	(1.43)	1.007	(22.84)***	0.226	(3.77)***	0.325	(4.42)***	−0.263	(4.43)***	3501	0.17
3	−0.002	(1.37)	1.037	(23.42)***	0.108	(1.92)*	0.451	(6.69)***	−0.269	(5.20)***	3518	0.18
4	0.002	(1.42)	1.049	(24.19)***	0.142	(2.22)**	0.313	(4.62)***	−0.147	(2.68)***	3439	0.20
5	0.006	(3.68)***	1.136	(21.23)***	0.095	(1.46)	0.258	(3.48)***	−0.192	(3.41)***	3241	0.18
Three years after portfolios formed												
1	0.001	(0.48)	1.040	(20.45)***	0.147	(2.60)***	0.623	(6.50)***	−0.434	(7.78)***	3273	0.17
2	−0.001	(0.44)	1.023	(20.93)***	0.191	(3.37)***	0.443	(5.05)***	−0.390	(7.10)***	3269	0.16
3	0.000	(0.07)	1.172	(22.31)***	0.134	(2.52)**	0.677	(8.25)***	−0.287	(5.62)***	3429	0.19
4	0.006	(3.39)***	1.088	(23.60)***	0.210	(3.51)***	0.536	(6.46)***	−0.206	(3.60)***	3242	0.17
5	0.007	(3.34)***	1.081	(18.00)***	0.130	(1.85)*	0.276	(2.67)***	−0.337	(5.23)***	2996	0.15

(continued on next page)

TABLE 6 (continued)

Panel C: Factor Model Regressions for Mean Monthly Risk-Adjusted Return in Excess of Market for Portfolios Formed Based on Residual IT/Sales Levels from Lowest (Portfolio 1) to Highest (Portfolio 5)[c]

$$R_{it} - R_{ft} = a + b_1[R_{mt} - R_{ft}] + b_2SMB_t + b_3HML_t + b_4UMD_t + e_{it}$$

Portfolio	a	t(a)	b1	t(b1)	b2	t(b2)	b3	t(b3)	b4	t(b4)	n	Adj. R^2
One year after portfolios formed												
1	0.000	(0.19)	1.107	(22.45)***	0.039	(0.71)	0.254	(3.91)***	−0.226	(3.35)***	3531	0.16
2	0.002	(1.36)	0.985	(20.34)***	0.031	(0.62)	0.123	(1.92)*	−0.245	(4.32)***	3388	0.16
3	−0.001	(0.68)	1.006	(19.95)***	0.180	(3.46)***	0.317	(4.58)***	−0.152	(2.66)***	3592	0.16
4	0.000	(0.18)	1.043	(20.87)***	0.045	(0.77)	0.345	(4.76)***	−0.229	(3.60)***	3480	0.16
5	0.003	(1.68)*	1.046	(20.74)***	0.220	(3.66)***	0.350	(5.25)***	−0.163	(2.64)***	3372	0.15
Two years after portfolios formed												
1	0.002	(0.96)	1.020	(21.81)***	0.056	(0.96)	0.332	(4.53)***	−0.241	(4.01)***	3399	0.16
2	−0.001	(0.63)	0.957	(21.09)***	0.038	(0.69)	0.245	(3.41)***	−0.317	(6.16)***	3329	0.17
3	−0.001	(0.50)	0.967	(19.81)***	0.199	(3.21)***	0.371	(5.03)***	−0.193	(3.47)***	3500	0.16
4	0.001	(0.33)	1.081	(23.85)***	0.225	(3.56)***	0.437	(5.76)***	−0.334	(5.82)***	3287	0.19
5	0.005	(3.20)***	1.094	(22.09)***	0.158	(2.54)**	0.344	(5.01)***	−0.222	(4.30)***	3218	0.18
Three years after portfolios formed												
1	−0.000	(0.09)	1.060	(22.75)***	0.060	(1.06)	0.426	(4.95)***	−0.260	(4.75)***	3230	0.19
2	0.003	(1.89)*	1.042	(19.10)***	0.100	(1.73)*	0.457	(4.79)***	−0.370	(6.51)***	3219	0.16
3	0.003	(1.74)*	1.049	(20.01)***	0.235	(4.08)***	0.717	(8.29)***	−0.319	(5.98)***	3259	0.16
4	−0.001	(0.35)	1.176	(22.26)***	0.223	(3.48)***	0.579	(6.20)***	−0.414	(6.89)***	3096	0.18
5	0.006	(3.37)***	1.069	(19.50)***	0.191	(3.13)***	0.374	(3.93)***	−0.332	(5.65)***	3011	0.15

(continued on next page)

TABLE 6 (continued)

---

*,**,*** Significant at 10 percent, 5 percent, 1 percent, respectively. Robust absolute t-statistics in parentheses.

[a] Portfolios formed based on predicted IT budget to firm sales level (Table 3 Model 1); portfolio 1 represents lowest predicted IT budget and portfolio 5 represents highest.

[b] Portfolios formed based on actual IT budget to firm sales level; portfolio 1 represents lowest actual IT budget and portfolio 5 represents highest.

[c] Portfolios formed based on residual IT budget to firm sales level (actual IT budget minus predicted IT from Table 3 Model 1); portfolio 1 represents lowest residual IT budget and portfolio 5 represents highest.

R_{it} = monthly return for firm;
R_{ft} = risk-free return;
R_{mt} = monthly value-weighted market return;
SMB_t and HML_t = returns on Fama and French (1996) (factor-mimicking) portfolios for size and book to market, respectively; and
UMD_t = difference in returns on portfolios of past (six months ending in month $t-1$) winners and losers, where winners are the top quintile and losers are the bottom quintile of stocks.

As a robustness test of these findings, we regressed future annual returns on current actual IT budget values, controlling for risk with the Fama/French factors:

$$R_{it} - R_{ft} + \mathrm{a} + \mathrm{b}_1[R_{mt} - R_{ft}] + \mathrm{b}_2 SMB_t + \mathrm{b}_3 HML_t + \mathrm{b}_4 actual\ IT\ budget_{it-n} + \mathrm{e}_{it}, \tag{4}$$

and compared this to results obtained using predicted and residual IT budgets simultaneously:

$$R_{it} - R_{ft} = \mathrm{a} + \mathrm{b}_1[R_{mt} - R_{ft}] + \mathrm{b}_2 SMB_t + \mathrm{b}_3 HML_t + \mathrm{b}_4 predicted\_IT_{it-n} + \mathrm{b}_5 residual\_IT_{it-n} + \mathrm{e}_{it}, \tag{5}$$

where $R_{it} - R_{ft}$ is the annual return (compounded from monthly CRSP return data) minus the risk-free rate, $R_{mt} - R_{ft}$ is the corresponding annual value-weighted market return minus the risk-free rate, SMB are annual returns on factor-mimicking portfolios based on size, *HML* are the corresponding annual returns for portfolios based on book-to-market, *predicted_IT* is the context-driven predicted value of IT scaled by sales, *residual_IT* is the actual IT budget amount (scaled by sales) minus *predicted_IT*, and *n* varies from 1 to 3 to show the effect of IT budget amounts on future returns.[23]

Table 7 presents the results of the regressions based on Equations (4) and (5). In all four models, *actual_IT_budget* is significantly related to future returns, controlling for Fama/French risk factors; predicted_IT is significantly positively related to returns for each of the three future years, as well as the average for all three years, and significantly greater than the coefficient on *residual_IT* in all four models ($p < 0.01$, results not shown). The coefficient for *residual_IT* is therefore lower than the coefficient for actual IT budget in all three years. The *residual_IT* coefficient indicates that investors in firms that allocate more to their IT budget (for example, an additional 1 percent of sales) will on average enjoy excess returns of 1.172 percent each year for the subsequent three years. Separation of *residual_IT* into positive and negative values yields coefficients that are not significantly different (not tabulated). These results confirm that IT budget levels predict future shareholder returns. Shareholders of firms that budget more for IT than other firms in similar settings receive excess returns, even though much of the relation between IT budget levels and future market performance is driven by contextual factors. As with the financial performance results, the significant positive coefficients on *residual_IT* for two and three years ahead returns suggest a positive marginal effect for idiosyncratic IT budget amounts.

In summary, Tables 5–7 indicate that IT budget levels influence future market returns. This suggests that there may be unquantified risks associated with IT budgets not reflected in our model, and that as a result investors wait until the uncertainties associated with projected benefits of IT budgets are resolved, or resolved in part, before valuing them more fully.

Summary of Findings for IT Budget Levels and Firm Performance

Our analysis of the relation between IT budget levels and future firm performance yields two insights. First, budget levels that are consistent with the contextual factors studied do not generate higher performance than budget levels that are not, contrary to the prediction of contingency theory. We recognize that the *predicted_IT* benchmark values represent a linear combination of contextual variables; therefore, we examine the effect of *residual_IT*, gauging the value of the *predicted_IT* benchmark by the performance effect of departures from it. In almost every regression model, the coefficient on *residual_IT* is significantly positively related to future financial and market performance, with no difference in the coefficients for positive and negative residuals.[24]

---

[23] Values for *UMD* are not available for annual (versus monthly) observations.

[24] These results are robust to a variety of tests and alternative specifications, including scaling the *residual_IT* values by *actual IT* budget amounts.

TABLE 7

Annual Factor Model Regressions for Excess Annual Returns Comparing the Effect of Predicted IT/Sales, Residual IT/Sales, and Actual IT Budget/Sales Levels on Future Returns

	1 Year Ahead $retrf_{it+1}$		2 Years Ahead $retrf_{it+2}$		3 Years Ahead $retrf_{it+3}$		Average for 1 to 3 Years Ahead $retrf_{it+n}$	
				(a)				
$mktrf_{t+n}$	0.010	0.010	0.008	0.008	0.008	0.008	0.008	0.008
	(10.91)***	(11.59)***	(11.37)***	(11.78)***	(11.44)***	(12.18)***	(8.49)***	(8.93)***
SMB_{t+n}	0.006	0.007	0.003	0.003	0.002	0.002	−0.000	−0.000
	(2.52)**	(3.06)***	(3.64)***	(3.86)***	(2.88)***	(2.85)***	(0.02)	(0.13)
HML_{t+n}	0.002	0.001	0.005	0.005	0.005	0.005	0.005	0.005
	(1.28)	(0.98)	(8.72)***	(8.71)***	(8.98)***	(9.56)***	(7.69)***	(8.62)***
$predicted\_IT_{it}$	5.274		5.582		5.785		5.492	
	(5.39)***		(4.98)***		(4.69)***		(5.92)***	
$residual\ IT_{it}$	0.458		1.593		1.230		1.172	
	(0.83)		(3.03)***		(1.61)***		(2.84)***	
$actual\ IT\ budget_{it}$		1.908		2.722		2.308		2.315
		(4.02)***		(5.92)***		(3.94)***		(6.28)***
Constant	−0.124	−0.048	−0.127	−0.064	−0.111	−0.038	−0.126	−0.060
	(4.82)***	(2.92)***	(4.20)***	(3.57)***	(3.64)***	(2.11)**	(5.13)***	(3.66)***
Observations	1383	1424	1337	1381	1271	1313	1255	1292
Adj. R^2	0.13	0.12	0.14	0.14	0.12	0.12	0.14	0.12

---

*,**,*** Significant at 10 percent, 5 percent, and 1 percent, respectively. Robust t-statistics in parentheses, adjusted for intrafirm correlation.

$t+n = t+1$, 2, or 3, indicates one, two, or three years ahead or the average of all three years as appropriate;
retrf = firm annual return (compounded from monthly returns) minus risk-free rate;

(continued on next page)

TABLE 7 (continued)

mktrf = value-weighted market return minus risk-free rate;
SMB = performance of small stocks relative to big stocks (SMB, Small Minus Big);
HML = the performance of value stocks relative to growth stocks (HML, High Minus Low);
actual IT budget = actual budgeted IT scaled by sales, winsorized at 2 percent;
predicted_IT = predicted value from Model 1 Table 3; and
residual IT = actual IT budget minus predicted IT.

mktrf, *SMB*, and *HML* annual benchmark factors from Ken French's website.

Higher IT budgets are associated with higher performance regardless of how they compare to our proxy for aligned IT budgets, the *predicted_IT* benchmark, indicating it is not optimal for performance.[25] We discuss this further in the "Conclusion" section. Second, estimates of returns to IT in prior research may be inflated by the effects of omitted contextual variables that covary with IT. We find that these variables' aggregate effect (i.e., the *predicted_IT* coefficient) is significant, and exceeds the effect of IT after these effects are removed (i.e., the *residual_IT* coefficient).

V. LIMITATIONS

We also note some limitations of this study. Clearly, the self-reported survey data used for the analysis have several limitations. First, the data are not readily verifiable. Second, since the *InformationWeek* survey focused on larger companies, the data are not representative of all companies' IT budgets. In particular, the data do not include smaller, fast-growing companies, some of which are likely to invest heavily in IT. Notwithstanding such limitations, the *InformationWeek* data offer a unique opportunity to examine important resource allocation decisions. Furthermore, the *InformationWeek* survey and similarly compiled *ComputerWorld* data on IT expenditures have been used extensively in prior studies (e.g., Brynjolfsson and Hitt 1996; Lichtenberg 1995).[26]

We also recognize that the data are not recent, suggesting that different results might be obtained with later data if it were available. To test that possibility, we estimated more recent IT budget data using information about the number of each firm's IT employees that *InformationWeek* disclosed for 1996 to 2003.[27] This IT budget proxy, scaled by sales, remained significantly related to future performance consistent with the results shown in Tables 4–6. We call on future research to conduct this analysis on a more recent time period as the data become available to confirm that these results reflect current relations between IT budget levels, the determinants of those budget levels, and firm performance.

Since it is also possible that the results have been affected by abnormal IT budget patterns relating to Year 2000 requirements, we estimated Equations (1) and (2) with year dummy variables (results not shown). Additionally, we separately estimated the performance (Equation (2)) regressions for data from 1991 to 1994 and from 1995 to 1997 (results not shown). We found little difference in the results, confirming that neither the determinants nor consequences of IT budgets are driven by a potential Year 2000 effect.

Finally, the performance analysis indicates that the *predicted_IT* benchmark is not optimal for performance. This may be because salient variables have been omitted from the benchmark, the measures used for the variables are not sufficiently precise, or both.

VI. CONCLUSION

Contingency theory predicts that budgets are set on the basis of environmental, organizational, and technological factors. Researchers are only rarely able to obtain budget numbers (as opposed to actual realizations) to test this prediction for a large sample of firms, as was done in this study. The evidence presented herein contributes to management accounting research on budget formulation by demonstrating that several objectively measurable contextual factors affect budget levels for IT, one of the largest components of corporate spending.

---

[25] If *predicted_IT* budget levels are optimal, the *residual_IT* coefficient will be zero: negative *residual_IT* values will have a positive coefficient that will be offset by a negative coefficient for positive *residual_IT* values.

[26] Lichtenberg (1995) found the data from *InformationWeek* and *ComputerWorld* highly correlated, which argues for the accuracy of the data from both sources.

[27] Specifically, we estimated the following equation for 1996 and 1997 and then used the coefficient on the independent variables to estimate IT budget levels for 1998 to 2003: $\mathrm{Log}(\mathit{IT\ Budget}_{it}) = b_0 + b_1 \log(\mathit{Sales}_{it}) + b_2 \log(\mathit{IT\ Workers}_{it}) + e_{it}$.

The study presents the first empirical evidence that industries using IT primarily to automate or transform business processes have higher IT budget levels than those that use IT primarily to informate decision processes. This confirms that firms requiring robust technology platforms to enable business operations and/or having regularly to "reinvent" these platforms must spend more on IT than those that instead focus on capturing, analyzing, and providing access to data about business activities. This contributes to the AIS literature by increasing our understanding of a foundational framework within the IS literature, specifically the relative cost of deploying IT in each of its three industry strategic roles.

In particular, these findings have implications for CIOs and CFOs in evaluating IT budgets each year. Anecdotal evidence suggests that senior managers often employ industry average IT spending as a percentage of sales as a benchmark for setting their own IT budget levels, rather than explicitly adjusting this baseline to reflect a variety of firm- and industry-level contextual factors. To maximize the payoff from IT budgets, managers could consider these objectively measurable factors when setting their IT budgets and adjust them dynamically as factors change. More specifically, managers could run similar analyses to generate a more sophisticated IT budget model, using it as a benchmark for their firm's IT budget to identify and justify departures from the industry average. Thereafter, the variables driving the predicted figure could be updated and used as a tool to monitor and adjust dynamically the overall IT budget allocation. Future research could further investigate these and other contextual factors and the trade-offs made among them by managers. The IT context is potentially just one instance of the more general phenomenon. Since misaligned budgets are potentially pervasive, we call on future research to consider other areas (advertising, R&D, capital expenditures, maintenance, etc.) to assess the cost of misalignment.

These findings also show support for the relationship between IT budget levels and firm profitability and shareholder returns and extend those results by finding that IT's effect is a weighted average of the effects of two very different IT components: (1) the context-driven IT budget, and (2) the idiosyncratic IT budget. Since the context-driven IT budget component reflects the effect of contextual factors, the idiosyncratic component presents a more accurate estimate of the marginal impact of IT budget on performance. Prior research has focused on aggregate rather than idiosyncratic IT amounts, providing limited insight to CEOs, CFOs, and CIOs who wonder if they should spend more or less on IT than other firms. The findings indicate that contextual factors account for a substantial portion of the apparent returns to IT, but that incremental profits and shareholder returns remain positive after controlling for these factors and are consistent for budgets above and below the context-driven benchmark. Just as important, the analysis indicates that the performance benefits of IT budgets are not competed away within three years.

In this setting, contingency theory provides a framework for managers to develop a more sophisticated benchmark for IT budgets based on the context the firm faces. The performance analysis indicates, however, that this benchmark is not optimal for performance. While firms that budget well below the context-aligned benchmark enjoy positive returns to additional IT spending, so do firms that are above it, therefore the variables used to create the benchmark are not sufficient to discern an optimal IT budget level, if it exists. As noted in the "Limitations" section, this may be a result of the imprecision of the measures used, the effects of omitted variables, or both. To find the level of IT budget at which returns begin to decline, new measures will have to be developed and other contingencies measured. Recent research findings addressing the latter suggest that firms must have outstanding IT talent (Bharadwaj 2000), have aligned these investments with the firm's strategic directions (Chan et al. 2006), and have made business investments to complement the IT investments (Kohli and Devaraj 2004) to maximize their returns from IT. This presents an opportunity for future research.

Future research could also investigate why the market does not seem to respond to IT investments in an efficient manner. This could examine whether there is some specific risk or uncertainty associated with IT that has not been controlled or the stock market waits to see enhanced profit before appropriately valuing IT.

REFERENCES

Abernethy, M. A., and P. Brownell. 1999. The role of budgets in organizations facing strategic change: An exploratory study. *Accounting, Organizations and Society* 24: 189–204.

Achen, C. H. 2000. Why lagged dependent variables can suppress the explanatory power of other independent variables. Working paper, University of Michigan.

Anderson, M. C., R. D. Banker, and N. Hu. 2003. Returns on investment in information technology. *Proceedings of Twenty-Fourth International Conference on Information Systems*, 563–575, Seattle, Washington.

———, ———, and S. Ravindran. 2006. Value implications of investments in information technology. *Management Science* 52 (9): 1359–1376.

Armstrong, C., and V. Sambamurthy. 1999. Information technology assimilation in firms: The influence of senior leadership and IT infrastructures. *Information Systems Research* 10 (4): 304–327.

Besanko, D., D. Dranove, and M. Shanley. 2001. Exploiting a cost advantage and coping with a cost disadvantage. *Management Science* 47 (2): 221–235.

Bharadwaj, A. S., S. G. Bharadwaj, and B. R. Konsynski. 1999. Information technology effects on firm performance as measured by Tobin's q. *Management Science* 45 (7): 1008–1024.

———. 2000. A resource-based perspective on information technology capability and firm performance: An empirical investigation. *MIS Quarterly* 24 (1): 169–196.

Bhatt, G. D., and V. Grover. 2005. Types of information technology capabilities and their role in competitive advantage: An empirical study. *Journal of Management Information Systems* 22 (2): 253–277.

Broadbent, M., P. Weill, T. O'Brien, and B. S. Neo. 1996. Firm context and patterns of IT infrastructure capability. *Proceedings of International Conference on Information Systems*, 174–194, Cleveland, Ohio.

Brynjolfsson, E., and L. M. Hitt. 1996. Paradox lost? Firm-level evidence on the returns to information systems spending. *Management Science* 42 (4): 541–560.

———, and ———. 1998. Beyond the productivity paradox. *Communications of the ACM* 41 (8): 49–57.

Bureau of Economic Analysis. 2007. Table 5.3.5: Private fixed investments by type. Available at: http://www.bea.gov/bea/dn/nipaweb/TableView.asp?SelectedTable=128&FirstYear=2006&LastYear=2008&Freq=Qtr.

Burns, T., and G. M. Stalker. 1961. *The Management of Innovation.* London, U.K.: Tavistock.

Carr, N. G. 2003. IT doesn't matter. *Harvard Business Review* 81 (5): 41–49.

Chan, L. K. C., J. Karceski, and J. Lakonishok. 1998. The risk and return from factors. *Journal of Financial and Quantitative Analysis* 33 (2): 159–188.

———, J. Lakonishok, and T. Sougiannis. 2001. The stock market valuation of research and development expenditures. *The Journal of Finance* 56 (6): 2431–2456.

Chan, Y. 2000. IT value: The great divide between qualitative and quantitative and individual and organizational measures. *Journal of Management Information Systems* 16 (4): 225–261.

———, R. Sabherwal, and J. B. Thatcher. 2006. Antecedents and outcomes of strategic IS alignment: An empirical investigation. *IEEE Transactions on Engineering Management* 53 (1): 27–47.

Chatterjee, D., V. J. Richardson, and R. W. Zmud. 2001. Examining the shareholder wealth effects of new CIO position announcements. *MIS Quarterly* 25 (1): 43–70.

Cheng, Q. 2005. What determines residual income? *The Accounting Review* 80 (1): 85–112.

Covaleski, M. A., J. H. Evans, III, J. L. Luft, and M. D. Shields. 2003. Budgeting research: Three theoretical perspectives and criteria for selective integration. *Journal of Management Accounting Research* 15: 3–49.

Dedrick, J., V. Gurbaxani, and K. L. Kraemer. 2003. Information technology and economic performance: A critical review of the empirical evidence. *ACM Computing Surveys* 34 (1): 1–28.

Dehning, B., and V. J. Richardson. 2002. Returns on investments in information technology: A research synthesis. *Journal of Information Systems* 16 (1): 7–30.

———, ———, and R. W. Zmud. 2003. The value relevance of announcements of transformational information technology investments. *MIS Quarterly* 27 (4): 637–656.

Dewan, S., and H. Mendelson. 1998. Information technology and time-based competition in financial markets. *MIS Quarterly* 44 (2): 595–609.

———, S. C. Michael, and C. Min. 1998. Firm characteristics and investments in information technology: Scale and scope effects. *Information Systems Research* 9 (3): 219–232.

———, C. Shi, and V. Gurbaxani. 2007. Investigating the risk-return relationship of information technology investment: Firm-level empirical analysis. *Management Science* 53 (12): 1829–1842.

Dos Santos, B. L., K. Peffers, and D. Mauer. 1993. The impact of information technology investment announcements on the market value of the firm. *Information Systems Research* 4 (1): 1–23.

Drazen, R., and A. H. Van de Ven. 1985. Alternative forms of fit in contingency theory. *Administrative Science Quarterly* 30: 514–539.

Efron, B., and R. J. Tibshirani. 1993. *An Introduction to the Bootstrap*. New York, NY: Chapman & Hall.

Fama, E. F., and K. R. French. 1996. Multifactor explanations of asset pricing anomalies. *The Journal of Finance* 51 (1): 55–84.

Francis, J., and K. Schipper. 1999. Have financial statements lost their relevance? *Journal of Accounting Research* 37 (2): 319–352.

———, R. LaFond, P. M. Olsson, and K. Schipper. 2004. Costs of equity and earnings attributes. *The Accounting Review* 79 (4): 967–1010.

Froot, K. A. 1989. Consistent covariance matrix estimation with cross-sectional dependence and heteroskedasticity in financial data. *Journal of Financial Quantitative Analysis* 24 (3): 333–356.

Galbraith, J. R. 1977. *Organization Design*. Reading, MA: Addison-Wesley.

Goncalves, S., and H. White. 2005. Bootstrap standard error estimates for linear regression. *Journal of the American Statistical Association* 100 (September): 970–979.

Gordon, R. J. 2003. Hi-tech innovation and productivity growth: Does supply create its own demand? Working paper 9437, National Bureau of Economic Research.

Gurbaxani, V., and S. Whang. 1991. The impact of information systems on organizations and markets. *Communications of the ACM* 34 (1): 59–73.

Hitt, L. M., and E. Brynjolfsson. 1996. Productivity, business profitability, and consumer surplus: Three different measures of information technology value. *MIS Quarterly* 20 (2): 121–141.

InformationWeek. 2001. *InformationWeek* 500 survey. Figure 6 14. *InformationWeek* (September 17).

Jacquemin, A. P., and C. H. Berry. 1979. Entropy measure of diversification and corporate growth. *Journal of Industrial Economics* 27 (4): 359–370.

Joseph, K., and V. J. Richardson. 2002. Free cash flow, agency costs and the affordability method of advertising budgeting. *Journal of Marketing* 66 (1): 94–107.

Kamien, M. I., and N. L. Schwartz. 1978. Self-financing of an R&D project. *The American Economic Review* 68 (3): 252–261.

Kaplan, R. S., and D. P. Norton. 2001. *The Strategy Focused Organization: How Balanced Scorecard Companies Thrive in the New Business Environment*. Boston, MA: Harvard Business School Press.

———, and ———. 2004. *Strategy Maps*. Boston, MA: Harvard Business School Press.

Kearns, G. S. 2004. A multi-objective, multi-criteria approach for evaluating IT investments: Results from two case studies. *Information Resources Management Journal* 17 (1): 37–62.

Kim, C. 2001. Firm diversification and earnings volatility: An empirical analysis of U.S.-based MNCs. *American Business Review* 19 (1): 26–38.

Kobelsky, K., S. Hunter, and V. J. Richardson. 2006. Information technology, contextual factors, and the volatility of firm performance. Working paper, Baylor University.

Kohli, R., and S. Devaraj. 2004. Realizing the business value of information technology investments: An organizational process. *MISQ Executive* 3 (1): 53–68.

Lawrence, P. R., and J. W. Lorsch. 1967. *Organization and Environment; Managing Differentiation and Integration*. Boston, MA, and Homewood, IL: R. D. Irwin.

Lee, J. H., and U. Bose. 2002. Operational linkage between diverse dimensions of information technology investments and multifaceted aspects of a firm's economic performance. *Journal of Information Technology* 17 (3): 119–131.

Lev, B., and T. Sougiannis. 1996. The capitalization, amortization and value-relevance of R&D. *Journal of Accounting and Economics* 21 (1): 107–138.

Lichtenberg, F. R. 1995. The output contribution of computer equipment and personnel: A firm level analysis. *Economics of Innovation and New Technology* 3 (3/4): 201–217.

Luft, J. L., and M. D. Shields. 2003. Mapping management accounting: Graphics and guidelines for theory-consistent empirical research. *Accounting, Organizations and Society* 28: 169–249.

March, J. G., and H. Simon. 1958. *Organizations*. New York, NY: Wiley.

Melville, N., K. Kraemer, and V. Gurbaxani. 2004. Review: Information technology and organizational performance: An integrative model of IT business value. *MIS Quarterly* 28 (2): 283–322.

Mintzberg, H. 1988. Crafting strategy. *Harvard Business Review* 66 (4): 66–75.

Mohanram, P. 2005. Separating winners from losers among low book-to-market stocks using financial statement analysis. *Review of Accounting Studies* 10 (2/3): 133–170.

Nyamori, R. O., M. H. B. Perera, and S. R. Lawrence. 2001. The concept of strategic change and implications for management accounting research. *Journal of Accounting Literature* 20: 62–83.

Oh, W., J. Kim, and V. J. Richardson. 2006. The moderating effect of context on the market reaction to IT investments. *Journal of Information Systems* 20 (1): 19–44.

Oliner, S. D., and D. E. Sichel. 2000. The resurgence of growth in the late 1990s: Is information technology the story? Working paper, Federal Reserve Board.

Pakko, M. R. 2002. Investment-specific technology growth: Concepts and recent estimates. *Review of the Federal Reserve Bank of St. Louis* 84 (6): 37–48.

Perry, S., and R. Grinaker. 1994. Earnings expectations and discretionary research and development spending. *Accounting Horizons* 8 (4): 43–51.

Pfeffer, J., and G. R. Salancik. 1978. *The External Control of Organizations: A Resource Dependence Perspective*. New York, NY: Harper & Row.

Piotroski, J. D. 2000. Value investing: The use of historical financial statement information to separate winners from losers. *Journal of Accounting Research* 38 (3): 1–40.

Porter, M. 1985. *Competitive Advantage: Creating and Sustaining Superior Performance*. New York, NY: Free Press.

Richardson, V. J., and R. W. Zmud. 2002. Systematic investor biases regarding stock market returns following information technology expenditures. Working paper, University of Kansas.

Ross, J. W., and P. Weill. 2002. Six IT decisions your IT people shouldn't make. *Harvard Business Review* 80 (11): 84–91.

Santhanam, R. 2003. Issues in linking information technology capability to firm performance. *MIS Quarterly* 27 (1): 125–153.

Schein, E. H. 1992. The role of the CEO in the management of change: The case of information technology. In *Transforming Organizations*, edited by T. A. Kochan and M. Useem. Oxford, U.K.: Oxford University Press.

Simons, R. 1995. *Levers of Control: How Managers Use Innovative Control Systems to Drive Strategic Renewal*. Boston, MA: Harvard Business School Press.

Slagmulder, R. 1996. A dynamic theory of the use of management control systems in achieving alignment between strategic capital investment decisions and strategy. *European Accounting Review* 5 (2): 390–396.

Stata Press. 2005. *Stata Reference Manual*. College Station, TX: Stata Press.

Stratopoulos, T., and B. Dehning. 2000. Does successful investment in information technology solve the productivity paradox? *Information & Management* 38 (2): 103–117.

Thompson, J. D. 1967. *Organizations in Action*. New York, NY: McGraw-Hill.

Wooldridge, J. M. 2003. *Introductory Econometrics: A Modern Approach.* 2nd edition. Mason, OH: Thomson South-Western.

Zhao, H., and S. Zou. 2002. The impact of industry concentration and firm location on export propensity and intensity: An empirical analysis of Chinese manufacturing firms. *Journal of International Marketing* 10 (1): 52–71.

THE ACCOUNTING REVIEW
Vol. 83, No. 4
2008
pp. 997–1040

American Accounting Association
DOI: 10.2308/accr.2008.83.4.997

The Value-Relevance of Cash Flows and Accruals: The Role of Investment Opportunities

Krishna R. Kumar
The George Washington University

Gopal V. Krishnan
Lehigh University

ABSTRACT: We examine the role of investment opportunities as a determinant of the relative importance of cash flows from operations (CFO) and accruals in firm valuation. We find that at low investment-opportunity levels, CFO value-relevance increases with investment opportunities. When investment opportunities are high, accrual value-relevance declines as investment opportunities increase. Consequently, earnings value-relevance first varies directly and then inversely with investment opportunities. We show that the increase in CFO value-relevance is consistent with cost differentials between internal and external financing causing CFO to be an increasingly important determinant of the realization of investment opportunities. The decline in accrual value-relevance at high investment-opportunity levels appears to be attributable to accounting measurement deficiencies.

Keywords: *capital markets; investment opportunities; earnings; cash flows from operations; accruals; value-relevance.*

Data Availability: *Data used in this study are available from the CRSP and Compustat databases and other public sources.*

JEL Classifications: *G12; G14; M41.*

We gratefully acknowledge helpful comments and suggestions from Anwer Ahmed, Bill Baber, Steve Christophe, Steve Hansen, Chris Jones, Sok-Hyon Kang, Michael Kirschenheiter, Lihong Liang, Fred Lindahl, James Livingstone, Jim Patton, Mary Sullivan, and Kumar Visvanathan, two anonymous referees, and Patricia Dechow (editor). We thank Lucy Lim for her able research assistance. We also thank participants for comments at accounting research workshops at The American University, Baruch College–CUNY, City University of Hong Kong, George Mason University, The George Washington University, Georgetown University, and Temple University; at the 2004 Annual Congress of the European Accounting Association held at Prague, Czech Republic; and at the 2005 American Accounting Association Annual Meeting in San Francisco. Krishna Kumar acknowledges financial support provided through the 2003 Crain Fellowship program at The George Washington University.

Editor's Note: This paper was accepted by Patricia M. Dechow.

Submitted: February 2005
Accepted: December 2007
Published Online: July 2008

I. INTRODUCTION

We examine how the value-relevance of cash flows from operations (CFO) and accruals varies with investment (growth) opportunities. The superiority of accrual-accounting-based earnings relative to cash flows in assessing firm value is a key element of the conceptual foundation of U.S. Generally Accepted Accounting Principles (GAAP; see Statement of Financial Accounting Concepts No. 1, FASB 1978). Consistent empirical evidence that accruals are a value-relevant component of earnings supports this perspective (see, for example, Rayburn 1986; Dechow 1994; Barth et al. 1999). How the relative impact of the two components of earnings (CFO and accruals) compare and what the determining factors are, is not yet well understood, however. The present study considers the role of investment opportunities in determining this relative impact.

Bernard and Stober (1989, 648), who are among the first to suggest that the valuation implications of CFO and accruals vary with circumstances, argue for "a better understanding of the economic context in which the implications of detailed earnings components are interpreted." Much of the research that follows Bernard and Stober (1989) focuses on how earnings properties, such as persistence, impact the value-relevance of earnings components (see, for example, Ali 1994; Cheng et al. 1996; Pfeiffer et al. 1998; Sloan 1996). While such studies provide important insights into the value-relevance of earnings, with few exceptions (for example, Anthony and Ramesh 1992), most studies do not consider underlying economic factors that potentially determine earnings properties. We focus on investment opportunities because they are a significant and growing part of corporate assets.[1] A firm's growth potential often substantially derives from its investment opportunities. If the value-relevance of earnings components varies with such growth opportunities, then evidence on these relations can be useful in assessing firm value.

Currently, we know of no empirical evidence on relations between investment opportunities and the value-relevance of earnings components in general or CFO and accruals in particular.[2] Furthermore, even extant research on relations between investment opportunities and the value-relevance of *aggregate* earnings is conflicting. Collins and Kothari (1989) document positive associations between earnings response coefficients (ERCs) and the ratio of the market-to-book-value of equity—their proxy for investment opportunities—whereas Ahmed (1994) shows that ERCs vary inversely with investment in research and development. Amir and Lev (1996) find that neither earnings nor CFO is value-relevant in the wireless communications industry, except when considered concurrently with nonfinancial information.

Our analysis is motivated by three perspectives or hypotheses about how and why the value-relevance of CFO and accruals varies with investment opportunities. The *growth information hypothesis relies* on Collins and Kothari's (1989) proposition that investors learn from current earnings innovations about the capacity of future growth opportunities to generate abnormal profits. The *internal resource hypothesis* presumes that cost differentials between internal and external financing arise due to information asymmetries, agency costs, and transaction costs (Myers and Majluf 1984; Kaplan and Zingales 1997; Hubbard 1998) and cause internal funding provided by CFO to be an increasingly important determinant of whether growth opportunities are pursued. These two hypotheses predict that both CFO and accrual response coefficients vary directly with investment opportunities. The *noisy measure hypothesis* posits that error in measuring both CFO and accruals increases with investment opportunities due to deficiencies in accounting practice, causing investors to reduce their reliance on these numbers. Thus, both CFO and accrual response coefficients vary inversely with investment opportunities.

---

[1] Although investment opportunities are not directly observable, data on actual investment levels for U.S. corporations provide indirect evidence suggesting that investment opportunities are substantial in magnitude. Gu and Lev (2004) report average market-to-book ratios for S&P 500 firms in excess of 4.5, indicating that assets-in-place comprise a relatively small portion of corporate assets. Investment opportunities potentially represent a significant part of this book-market value differential, although understated book values and economic rents are also likely contributing factors. Furthermore, corporate capital expenditures, and expenditures on intangible assets such as product and process technology, brand loyalty, and human resource assets currently amount to about 20 percent of GDP and are four times the amount required to replace the consumption of fixed capital (Federal Reserve Board 2004, Tables F.102 and R.102; Nakamura 2003).

[2] A growing body of research examines the implications of growth opportunities for security valuation and related parameters. For example, Anderson and Garcia-Feijoo (2006) consider implications of growth opportunities for expectations of future stock returns and equity risk. Lev and Thiagarajan (1993) and Chen and Zhang (2007) consider the relevance of growth opportunities for contemporaneous security returns. However, such studies do not investigate earnings components. Moreover, the scope of their analysis of explanations for the value-relevance of growth opportunities is more limited than the current study.

Different factors may dominate across different levels of investment opportunities, thus producing non-monotonic variations in CFO and accrual response coefficients over the entire growth-opportunities range. We use quadratic model specifications to accommodate such non-monotonic relations and provide empirical evidence on the relative importance of the three factors at different investment-opportunity levels.

We find that, at low investment-opportunity levels, CFO response coefficients increase with investment opportunities, consistent with both the *growth information hypothesis* and the *internal resource hypothesis*. At high investment-opportunity levels, accrual response coefficients decline as growth opportunities increase, suggesting that the *noisy measure hypothesis* prevails at these levels. Trends in accrual response coefficients at low investment-opportunity levels and in CFO response coefficients at high investment-opportunity levels are not statistically significant. The aggregate effect is that ERCs first vary directly with investment opportunities and then inversely.

We conduct two additional tests to distinguish between the *internal resource* and *growth information hypotheses*. The first uses samples partitioned on the extent that assets acquired to exploit growth opportunities are intangible versus tangible. Firms with substantial intangible investments are both more difficult to monitor for outside investors and likely to be characterized by substantial earnings measurement problems. We find that, after controlling for investment opportunities, CFO response coefficients are higher and accrual response coefficients lower for firms with high intangible-intensive investments. These findings are consistent with the *internal resource* and the *noisy measure hypotheses*, respectively.

Second, we partition the sample based on the availability within a firm of liquid financial resources for exploiting investment opportunities. We predict that in the presence of financing cost differentials, the value-relevance of both CFO and accruals are greater when such financial resources are scarce. We find that at moderately high investment-opportunity levels, both CFO and accrual response coefficients are indeed higher when financial resources are scarce. These findings are consistent with the *internal resource hypothesis*.

This study incorporates several methodological improvements that potentially help resolve conflicting findings of prior studies. First, it uses a larger, more broad-based sample. Second, specifications of unexpected earnings, CFO, and accruals consider both transitory and permanent components. Third, the study incorporates a more comprehensive, empirically validated measure of investment opportunities. Finally, it allows for non-monotonic relations between ERCs and its components, and investment opportunities.

The study makes several contributions. First, to our knowledge, it is the first study to consider how information about the availability of cash flows as an internal financing resource informs assessments of firm value. Second, it reconciles conflicting results in prior research on ERC-investment-opportunities relations by documenting that ERCs first increase and then decline as investment opportunities increase. Third, the evidence it provides on how and why the relative importance of CFO and accruals in value assessment varies with investment opportunities is potentially useful to investors and analysts. Finally, the findings complement Amir and Lev's (1996) evidence on the importance of nonfinancial information, by documenting the usefulness of important *financial* variables, such as CFO, in the context of investment opportunities. A standard-setting implication of our findings is that additional disclosures that facilitate CFO assessment can benefit investors in large-investment-opportunity-set firms. At the same time, new accounting standards designed to generate more value-relevant accruals can be useful for investors in such firms. These implications are relevant in light of the accounting failures of recent years that highlight weaknesses of corporate financial reporting and culminated in the Sarbanes-Oxley Act of 2002.

Our analysis follows a large body of return-earnings association studies in assuming market efficiency. However, recent research has uncovered a number of apparent inefficiencies. Of particular relevance to the present context is Sloan's (1996) finding that investors fail to fully consider the lower persistence of accruals relative to CFO in pricing the two earnings components. Our results may be biased and, therefore, should be interpreted with caution to the extent that such mispricing of securities occurs and is correlated with investment opportunities.

The paper's next section discusses the three perspectives on how the value-relevance of CFO, accruals, and earnings varies with investment opportunities. Section III presents the research design, variable measurement, and empirical methods, including features designed to address limitations of relevant prior studies. Sample selection, data sources, and descriptive statistics are covered in Section IV. Results are in Section V and conclusions in Section VI.

II. HYPOTHESES

The Growth Information Hypothesis

Collins and Kothari (1989) argue that current period earnings can indicate the potential for above-normal earnings (economic rents) from future investments. If so, then investors' revisions of expectations for such future economic rents in response to current unexpected earnings are likely to be larger when opportunities for rent-producing future investments are more substantial. In other words, investors learn about the value of future investments from current abnormal earnings, and such earnings-based value reassessments—that is, ERCs—increase with investment opportunities. *Ceteris paribus*, CFO and accruals being components of earnings, CFO and accrual response coefficients also increase with investment opportunities.

Sloan (1996) finds accruals to be less informative than CFO about the earnings potential of current operations. If this finding extends to investment opportunities, then accruals are less informative than CFO about the earnings potential of investment opportunities. The *growth information* hypothesis, stated in alternate form, predicts as follows.

H1C: CFO response coefficients increase with investment opportunities.

H1A: Accrual response coefficients increase with investment opportunities.

$H1_{Diff}$: CFO response coefficients increase at a faster rate with investment opportunities than accrual response coefficients.

Together, H1C and H1A imply the following:

H1E: Earnings response coefficients increase with investment opportunities.

The Internal Resource Hypothesis

Firms need cash in order to exploit investment opportunities. Cash can be obtained from internal resources or through external financing. In perfect and complete markets, financing choices do not affect investment decisions or firm value (Modigliani and Miller 1958). However, market frictions, such as information asymmetries, agency costs, and transaction costs, increase the cost of external capital relative to internal capital (Jensen and Meckling 1976; Myers and Majluf 1984; Oliner and Rudebusch 1992). Such cost differentials arise because suppliers of external capital (potential future investors) are less informed than managers about investment opportunities and lack the power to ensure that managers act in their interest. Internal capital—capital generated from the firm's operations—accrues to current shareholders ("old" shareholders in Myers and Majluf's [1984] terminology), who can better monitor and discipline managers through governance mechanisms such as the board of directors. If such oversight mechanisms are effective, and managers act in the interest of current shareholders, then information and agency costs faced by external suppliers of capital are more substantial than those for internal capital.

In the presence of differences in financing cost, the availability of internal resources to pursue investment opportunities increases firm value. This gain in value comes both from substituting lower-cost internal capital for higher-cost external capital in positive net-present-value (NPV) investments, and from previously negative NPV projects becoming viable (positive NPV) with the availability of internal resources.

Holding internal financing constant, the need for external financing increases as investment opportunities increases. If external financing is not collateralized, then marginal information and agency costs of external financing increase with the level of financing (Kaplan and Zingales 1997, 174; Hubbard 1998, 197). Governance mechanisms enable such costs to be lower for current shareholders than new investors, and to increase at a lower rate. Thus, cost differentials between internal and external financing, and the marginal contribution of internal financing to firm value increase with investment opportunities.

CFO is a primary source of internal financing. Unexpected changes in CFO potentially cause investors to reassess the amount of lower-cost internal resources available to realize marginal investment opportunities, or to substitute for higher-cost external capital. If so, then stock price revisions will follow such reassessments and correlate positively with unexpected CFO. Moreover, because of higher cost differentials between internal and external financing when investment opportunities are large, such reassessments will be greater for large-investment-opportunity-set firms than for small-investment opportunity-set firms, holding unexpected CFO constant. In other words, stock price responses to unexpected CFO (that is, CFO response coefficients) are predicted to increase with investment opportunities. To the extent that earnings comprise CFO, ERCs are predicted to increase with investment opportunities. The *internal resource hypothesis* also predicts that accrual response coefficients are positive, because accruals potentially inform investors about CFO in future periods, and consequently, the likelihood of realization of investment opportunities in the future. However, accrual response coefficients are likely to be smaller than CFO response coefficients, because investment opportunities expire, and thus fewer investment opportunities are expected to be available for future CFO. Furthermore, uncertainties about both future investment opportunities and future CFO are greater than uncertainties about current investment opportunities and CFO. Finally, future CFO must be discounted.

The predictions of the *internal resource hypothesis* are summarized as follows.

H2C: CFO response coefficients increase with investment opportunities.

H2A: Accrual response coefficients increase with investment opportunities.

$H2_{Diff}$: CFO response coefficients increase at a faster rate with investment opportunities than accrual response coefficients.

The following hypothesis follows from H2C and H2A:

H2E: Earnings response coefficients increase with investment opportunities.

The Noisy Measure Hypothesis

Generally accepted accounting principles (GAAP) require that R&D, advertising, and other expenditures incurred for developing intangible assets be classified as operating, and not investing, cash flows. As a result, reported CFO does not represent cash flows from operating activities alone, but from a mix of operating and investing activities. Furthermore, intangible-investment-related costs are typically expensed immediately, and not capitalized and amortized. Even when the costs are capitalized—for purchased patents, copyrights, or R&D—amortization is arbitrary. Dechow (1994) notes that accruals enhance the value-relevance of earnings by addressing timing and matching problems. However, when intangibles are expensed or arbitrarily amortized, the effectiveness of accruals in addressing timing and matching problems is compromised.

Thus, the accounting treatment of intangible investments results in measurement error in both CFO and accruals.[3] Lack of detailed disclosures about such expenditures compromises the ability to estimate and undo the measurement error. If creating and exploiting investment opportunities entails significant investments in such intangibles, then the measurement errors in CFO, accruals, and earnings vary directly with investment opportunities. If so, then investors increasingly rely on alternative information sources to assess value. As such, the value-relevance of the three financial measures decline as investment opportunities increase.

The predictions of the *noisy measure hypothesis* are as follows.

H3C: CFO response coefficients decline as investment opportunities increase.

H3A: Accrual response coefficients decline as investment opportunities increase.

The following hypothesis follows from H3C and H3A:

H3E: Earnings response coefficients decline as investment opportunities increase.

Summary of Hypotheses

Exhibit 1, Panel A summarizes the implications of the three hypotheses. Prior studies consider either the *growth information hypothesis* (Collins and Kothari 1989; Bodnar and Weintrop 1997) or the *noisy measure hypothesis* (Ahmed 1994; Amir and Lev 1996). We are unaware of studies that consider either the *internal resource hypothesis* or all three hypotheses concurrently.[4]

Individually, each hypothesis predicts monotonic relations between investment opportunities and response coefficients. When multiple effects are present, different effects may dominate at different investment-opportunity levels, causing non-monotonic relations. Our research design accommodates such relations.

---

[3] Prior studies such as Ahmed (1994) and Amir and Lev (1996) also point to the accounting treatment of investments that promote the (internal) development of intangible assets as a potential source of measurement error in earnings and accruals. However, few studies recognize the adverse impact of such GAAP policies on the value-relevance of CFO.

[4] Johnson and Lee (1994) consider the role of CFO as an internal cash resource in predicting one-year-ahead earnings. The *internal resource hypothesis* in the present study differs from Johnson and Lee (1994) in several important ways. First, because returns reflect expectation revisions for all future earnings, the returns association approach of the present study offers a more comprehensive analysis than one focusing on predicting a particular year's earnings. Second, Johnson and Lee (1994) consider the role of financing constraints *after controlling for* a firm's investment opportunities. The current study focuses on investment opportunities, and considers cost differentials in financing them. Finally, unlike the present study, Johnson and Lee (1994) do not consider CFO's role as an internal resource concurrently with other hypotheses, such as the *growth information* and *noisy measure* hypotheses.

EXHIBIT 1
Summary of Hypotheses and Their Predictions

Panel A: For Aggregate Sample

	Predictions for Associations between Investment Opportunities and...			
Hypothesis	**Cash Flow Response Coefficients (CRCs)**	**Accrual Response Coefficients (ARCs)**	**Earnings Response Coefficients (ERCs)**	**Predictions for Differences between CRCs and ARCs (CRC – ARC)**
Growth Information Hypothesis	H1C: Positive	H1A: Positive	H1E: Positive	$H1_{Diff}$: Positive
Internal Resource Hypothesis	H2C: Positive	H2A: Positive	H2E: Positive	$H2_{Diff}$: Positive
Noisy Measure Hypothesis	H3C: Negative	H3A: Negative	H3E: Negative	No prediction

Panel B: For Partitions by Intangible Intensity[a]

	Holding Investment Opportunities Constant, ...	
Hypothesis	**CRCs are...**	**ARCs are...**
Internal Resource Hypothesis	H4C: higher when intangible intensity is high	H4A: higher when intangible intensity is high
Noisy Measure Hypothesis	H5C: lower when intangible intensity is high	H5A: lower when intangible intensity is high

Panel C: For Partitions by the Availability of Excess Liquid Resources[a]

	Holding Investment Opportunities Constant, ...	
Hypothesis	**CRCs are ...**	**ARCs are ...**
Internal Resource Hypothesis	H6C: higher when excess alternative internal liquid financial resources are low	H6A: higher when excess alternative internal liquid financial resources are low

---

[a] Intangible-intensity and excess alternative liquid financial resources are defined in Exhibit 2.

Distinguishing among the Hypotheses

The *growth information hypothesis* and the *internal resource hypothesis* generate identical predictions for how CFO, accrual, and earnings response coefficients vary with investment opportunities. We conduct two additional tests to distinguish between these hypotheses.

The Intangible Intensity of Investments

First, we partition the sample based on the nature of assets required to pursue investment opportunities. Investment opportunities may require investments in tangible assets such as land, buildings, and equipment, or in intangibles such as intellectual property, knowledge, or market power. Managers' actions and their consequences are less observable when assets acquired are intangible rather than tangible (Smith and Watts 1992). Consequently, information asymmetries and agency costs are higher for intangible investments. The *internal resource hypothesis* predicts that the advantage of internal capital over external capital is greater for intangible investments. Hence, security price responses to CFO are more substantial when intangible investment is required. As noted earlier, predictions for CFO response coefficients under the *internal resource hypothesis* extend to accrual response coefficients. Thus, accrual response coefficients are also predicted to be higher under this hypothesis for intangible than for tangible investments.

The *growth information hypothesis*, which posits that investors learn from current performance about economic rents in future investment opportunities, does not distinguish between investment opportunities acquired through intangible versus tangible investments. Therefore, it makes no predictions about how relations between investment opportunities, and CFO and accrual response coefficients vary with intangible intensity.

Finally, as noted earlier in the discussion on the *noisy measure hypothesis*, measurement error in CFO and accruals is more substantial for intangible investments. If so, then both CFO and accrual response coefficients are smaller when investments are intangible-intensive than when tangible-intensive. These predictions lead to the following hypotheses. The first two (H4C and H4A) follow from the *internal resource hypothesis* and the last two (H5C and H5A) from the *noisy measure hypothesis*. Exhibit 1, Panel B presents a summary table.

H4C: Conditional on investment opportunities, CFO response coefficients are higher when investments are intangible intensive than when they are primarily in tangible assets.

H4A: Conditional on investment opportunities, accrual response coefficients are higher when investments are intangible intensive than when they are primarily in tangible assets.

H5C: Conditional on investment opportunities, CFO response coefficients are lower when investments are intangible intensive than when they are primarily in tangible assets.

H5A: Conditional on investment opportunities, accrual response coefficients are lower when investments are intangible intensive than when they are primarily in tangible assets.

The Availability of Liquid Financial Resources

The *internal resource hypothesis* presumes that cost differentials between internally and externally sourced capital cause CFO to be a determinant of the viability of valuable investment opportunities. Consequently, unexpected CFO causes reassessments of both the likelihood of investment-opportunity realization and firm value. However, the degree that the likelihood of investment-opportunity realization is contingent on unexpected CFO is also conditional on the availability of alternative internal financial resources to fund investments. In particular, realizations of investment opportunities are less sensitive to CFO *surprises* when either substantial liquid assets (e.g., cash or marketable securities) are available or there are *expectations* of substantial CFO.

Neither the *growth information hypothesis* nor the *noisy measure hypothesis* offer predictions regarding relations between CFO response coefficients and the availability of internal liquid resources. Thus, evidence in support of the following hypotheses potentially distinguishes the *internal resource hypothesis* from the others. The accrual response coefficients hypothesis (H6A) follows from the CFO response coefficients hypothesis (H6C) just as H3A follows from H3C. Exhibit 1, Panel C summarizes the hypotheses.

H6C: Conditional on investment opportunities, CFO response coefficients are higher for firms with a deficit of liquid financial resources for investment-opportunity realization than for firms with an excess of such resources.

H6A: Conditional on investment opportunities, accrual response coefficients are higher for firms with a deficit of liquid financial resources for investment-opportunity realization than for firms with an excess of such resources.

III. RESEARCH DESIGN, MODEL SPECIFICATIONS, AND VARIABLES

Primary Research Design

Studies investigating relations between ERCs and growth opportunities typically adopt model specifications of the following form. Parameter estimates a_2 are the principal focus.

$$CAR = a_0 + a_1 UE + a_2 IOS \times UE + \sum_C a_C \times \text{control\_variables}_C + \varepsilon \qquad (1)$$

where firm and year subscripts are suppressed, and:

CAR = cumulative abnormal returns during the disclosure period;
UE = unexpected earnings relative to expectations at the beginning of the fiscal period;
IOS = investment opportunities in the fiscal period;
$\text{control\_variables}_C$ = variables to control for potentially correlated factors;
$a_0, a_1, a_2, \ldots, a_C$ = parameter estimates; and
ε = error term.

As indicated in Section I, conflicting findings in prior studies of relations between ERCs and investment opportunities are potentially attributable to research design choices including sample selection, proxies for unexpected earnings, CFO and accruals, and measures of investment opportunities. Collins and Kothari (1989) use a sample of New York Stock Exchange (NYSE) firms, requiring at least eight years of financial data to document positive associations between investment opportunities and ERCs. Small, new, high-growth firms are likely to be under-represented in this sample.[5] Ahmed (1994) uses a sample of manufacturing firms to document negative relations between investment opportunities and ERCs. If manufacturing firms substantially differ in their investment opportunities than non-manufacturing firms, then Ahmed's (1994) findings have limited generality.[6] Finally, Amir and Lev's (1996) finding that financial information lacks value-relevance may also not apply more generally because the study is limited to one industry. Moreover, their tests may lack power due to the small sample.

Both Collins and Kothari (1989), and Ahmed (1994) use earnings changes as unexpected earnings proxies. If earnings have transitory elements, then earnings changes measure unexpected earnings with error, and earnings response coefficients are biased (Ali and Zarowin 1992). Moreover, if measurement error in earnings is correlated with growth opportunities, then the bias in ERCs varies with investment opportunities and can distort associations between the two factors.[7]

Collins and Kothari (1989) use the market-to-book-ratio as a proxy for growth opportunities. This ratio may also proxy for economic rents from assets-in-place, or for expected returns (Ahmed

---

[5] In our sample, the market capitalization (net revenue) for the average NYSE-listed firm is \$4.8 (\$3.9) billion. This is significantly larger than the market capitalization (net revenue) for the average non-NYSE-listed firm of \$555.1 (\$404.7) million ($p < 0.01$). Moreover, non-NYSE firms have significantly larger average values than NYSE firms for our investment opportunities measure, *IOS*, as well as for each of its four components ($p < 0.01$ in each case). Thus, restricting the sample to NYSE firms can bias toward excluding firms with large investment opportunities. *IOS* is defined later in this section and its components are defined in Exhibit 2.

[6] In our sample, manufacturing firms (SIC codes 2000 through 3999) have significantly larger ($p < 0.01$) investment opportunities than non-manufacturing firms, as indicated by the composite measure *IOS* and three of its four components: investment intensity, the market-to-book ratio of assets, and R&D expenditures to total assets ratio (see Exhibit 2).

[7] Collins and Kothari (1989) use reverse regression in an effort to reduce measurement-error-related bias that potentially characterizes ERCs derived from direct regressions of excess returns on earnings changes. Reverse regression is not an option in the present study, where return responses to multiple earnings components are examined concurrently.

1994; Fama and French 1992; Lindenberg and Ross 1981). If so, then positive associations between ERCs and market-to-book-ratios documented in Collins and Kothari (1989) may be attributable to factors other than investment opportunities. Ahmed's (1994) growth opportunities measure, specified as the ratio of R&D investment to tangible investment, does not consider investments other than R&D, and is not validated by comparison with subsequent realized growth.

Three distinguishing features of the present study address these limitations. First, our sample includes all unregulated firms that have sufficient data on Compustat and CRSP files for at least two consecutive years between 1989 and 2001.[8] This procedure yields a more representative sample than prior studies, one that includes small, young firms. Second, our investment-opportunities measure, *IOS*, developed originally by Baber et al. (1996), combines four commonly used growth opportunities metrics—the ratio of the market-to-book-value of assets, firm growth rate, R&D intensity, and investment intensity—rather than rely on a single measure. Several key features of *IOS* are noteworthy: (1) the underlying metrics are similar to measures used in previous studies such as Collins and Kothari (1989) (market-to-book-ratio), Ahmed (1994) (R&D intensity), and Bodnar and Weintrop (1997) (revenue growth); (2) the metrics are selected, not arbitrarily, but through a step-wise regression process that culls them from 16 growth-opportunities metrics, based on their ability to predict the intensity of future investment activity; (3) aggregation of multiple proxies reduces measurement error; (4) if an individual component growth metric (for example the market-to-book ratio of total assets) is correlated with an omitted variable, then potential parameter estimation bias is mitigated because the component represents only a fraction of the aggregate measure; and (5) the investment-opportunities measure uses a parsimonious variable set and a short data time-series, thus reducing loss of observations to missing data.[9]

Third, we specify unexpected earnings, CFO and accruals to accommodate transitory components and mitigate potential bias in response coefficients. We do so by using current and lagged levels of earnings, CFO, and accruals, following Pfeiffer and Elgers (1999) and others, to assess earnings, CFO, and accrual response coefficients, respectively. The "current and lagged" specification is equivalent to the "changes and levels" specification (see Ali and Zarowin 1992; Brown et al. 1987; Lev and Zarowin 1999) and has an expository advantage.[10] Response coefficients are estimated by just one coefficient—that on current levels—rather than the sum of the coefficients on changes and levels.

Specification to Examine Relations between Investment Opportunities and Earnings Response Coefficients

We begin by investigating how ERCs vary with investment opportunities, in order to provide comparisons with prior studies, and to provide a frame of reference for the subsequent analysis of CFO and accrual response coefficients.

As Section II indicates, ERCs may increase or decrease with investment opportunities depending on which of the three hypotheses—*growth information, internal resource*, or *noisy*

---

[8] Regulated firms (utilities [SIC 49] and banking institutions [SIC 60]) are excluded in order to be consistent with Baber et al. (1996), whose investment opportunities measure we use.

[9] Specifically, the aggregate measure computed for year t is highly correlated with $t+1$ through $t+5$ realized investment intensity, revenue growth, and asset growth, where investment intensity and asset growth rate are as defined in Exhibit 2 and revenue growth rate is defined similarly to asset growth rate.

[10] Brown et al. (1987) recommend including multiple performance measures, such as earnings changes and levels, as proxies for unexpected performance when individual variables are measured with error in order to mitigate overall measurement error. Easton and Harris (1991) demonstrate that both earnings changes and levels are significant in explaining annual returns, and suggest that including both measures reduces measurement error in unexpected earnings. Ali and Zarowin (1992) show analytically that a specification in terms of both earnings changes and levels is obtained as an approximation for unexpected earnings when earnings are partly transitory and follow an IMA (1,1) process.

measure—dominates. Because, we have no theory to guide us on which effect dominates at what investment-opportunity levels, we consider non-monotonic relations between ERCs and growth opportunities by including quadratic interaction terms $E \times IOS^2$ and $lagE \times IOS^2$ in the model.[11,12] The empirical specification below is based on Expression (1).

$$CAR = \mathrm{b}_0 + \mathrm{b}_1 E + \mathrm{b}_2 lagE + \mathrm{b}_3 IOS + \mathrm{b}_4 E \times IOS + \mathrm{b}_5 lagE \times IOS + \mathrm{b}_6 IOS^2 + \mathrm{b}_7 E \times IOS^2 + \mathrm{b}_8 lagE \times IOS^2 + \sum_C \mathrm{b}_C \mathrm{control\_variables}_C + \sum_Y \mathrm{b}_Y D_Y + \sum_I \mathrm{b}_I D_I + \in_\mathrm{b} \qquad (2)$$

where year and firm subscripts are suppressed; variables are as defined in Exhibit 2; b_0, b_1, $\mathrm{b}_2,\ldots,\mathrm{b}_I$ are parameter estimates; and $\in_\mathrm{b}$ is the error term.

In Expression (2), current period earnings E and prior period earnings $lagE$ replace UE in Expression (1) to accommodate unexpected earnings with transitory (mean-reverting) components. By regrouping terms in Expression (2), we obtain Expression (2′):

$$CAR = (\mathrm{b}_0 + \mathrm{b}_3 IOS + \mathrm{b}_6 IOS^2) + (\mathrm{b}_1 + \mathrm{b}_4 IOS + \mathrm{b}_7 IOS^2)E + (\mathrm{b}_2 + \mathrm{b}_5 IOS + \mathrm{b}_8 IOS^2)lagE + \sum_C \mathrm{b}_C \mathrm{control\_variables}_C + \sum_Y \mathrm{b}_Y \mathrm{D}_Y + \sum_I \mathrm{b}_I \mathrm{D}_I + \in_b. \qquad (2')$$

Expression (2′) presents the coefficients on E and $lagE$ as nonlinear functions of investment opportunities. The ERC, holding control variables constant, is estimated as the expression $\mathrm{b}_1 + \mathrm{b}_4 IOS + \mathrm{b}_7 IOS^2$, the coefficient on E.[13] Model 3 in Table 3 follows the form of Expression (2′), except that coefficient subscripts are arranged in numerical order for ease of exposition.

In estimating *IOS*, we recompute factor loadings, rather than use Baber et al.'s (1996) potentially obsolete factor loadings to combine *IOS* components. *IOS* has a mean (standard deviation) of 0 (1) by construction. Including *IOS* and IOS^2 as main effects in Expression (2) ensures that coefficients of earnings variables are not biased by factors correlated with *IOS*.

In addition to growth opportunities, prior research identifies risk, earnings persistence, and interest rates as determinants of ERCs (Kormendi and Lipe 1987; Easton and Zmijewski 1989; Collins and Kothari 1989). Because these can be correlated with investment-opportunity measures, we mitigate potential bias in response coefficients by including *BETA*, *PERSIST*, and *INTRATE* as proxies for risk, earnings persistence, and interest rates respectively in Expression (2). These

---

[11] An alternative approach may be to partition the sample, using exploratory techniques such as cluster analysis, into subsets for which each of the three hypotheses dominates. However, the resulting partitions would be *ex post* and data-driven. Instead, as discussed in Section II, we use *ex ante* partitioning based on the intangible intensity of investments, and the availability of liquid financial resources, to distinguish between the *growth information* and *internal resource hypotheses*. We infer support for the *noisy measure hypothesis* from the slopes of relations between response coefficients and investment opportunities.

[12] As is noted later in the paper, quadratic specifications add complexity to the presentation, discussion, and interpretation of response coefficients. An alternative approach that accommodates non-monotonic relations uses piece-wise linear specifications. While piece-wise linear specifications may be somewhat easier to interpret because they comprise individual linear segments, they require the arbitrary selection by the researcher of break points or points of discontinuity. Therefore, although we repeat our analysis using piece-wise linear specifications as a robustness check, we present the findings for the quadratic specification as our primary results.

[13] Note that Expression (2′) is mathematically equivalent to the following, where earnings changes $\Delta E (= E - lagE)$ and levels E proxy for UE and in which the sum of the coefficients of ΔE and E is the ERC estimate.

$$CAR = (\mathrm{b}_0 + \mathrm{b}_3 IOS + \mathrm{b}_6 IOS^2) + (-\mathrm{b}_2 - \mathrm{b}_5 IOS - \mathrm{b}_8 IOS^2)\Delta E + ((\mathrm{b}_1 + \mathrm{b}_2) + (\mathrm{b}_4 + \mathrm{b}_5) IOS + (\mathrm{b}_7 + \mathrm{b}_8) IOS^2)E + \sum_C \mathrm{b}_C \mathrm{\ control\_variables}_C + \sum_Y \mathrm{b}_Y D_Y + \sum_I \mathrm{b}_I D_I + \in_b.$$

EXHIBIT 2
Variable Definitions[a]

CAR = the market-model-based cumulative residual stock return relative to the CRSP equally weighted NYSE, AMEX, NASD market index, aggregated over the one-year period beginning with the fourth month of the current fiscal year *t*; market model parameters are estimated over the year preceding the annual return window;

E = reported income before extraordinary items (#18) for the current fiscal year *t*, scaled by the beginning-of-period *t* market-value-of-equity (MVE) (#199 × #25);

lagE = reported income before extraordinary items for the prior fiscal year $t-1$, scaled by the beginning-of-period *t* MVE;

$\Delta E = E - \text{lag}E$;

CFO = cash flows from operations (CFO) (#308) for the current fiscal year *t*, scaled by the beginning-of-period MVE;

lagCFO = CFO for the prior fiscal year $t-1$, scaled by the beginning-of-period MVE;

ACC = accruals ((#18–#308) for the current fiscal year *t*, scaled by the beginning-of-period MVE;

lagACC = accruals for the prior fiscal year $t-1$, scaled by the beginning-of-period MVE;

IOS = a measure of investment opportunities estimated as the first principal component, as in Baber et al. (1996), from a factor analysis of investment intensity (*INVINT*), growth rate of the market value of total assets (*MVAGR*), the market-to-book ratio of total assets (*MKTBKASS*), and the ratio of research and development expense to total assets (*R&D*);

INVINT = investment intensity, measured as:

$$\sum_{i=t-m}^{i=t} \frac{[\text{Capital expenditures}(\#30) + \text{R\&D expense}(\#46) + \text{Acquisitions}(\#129)]_i}{[\text{Depreciation}(\#14)]_i}$$

where m = max[1,2], depending on data availability;

MVAGR = geometric mean annual growth rate of market value of assets, measured as:

$$\sqrt[n]{\frac{\text{Market value of total assets}(\#6 - \#60 + \#199 \times \#25)_t}{\text{Market value of total assets}(\#6 - \#60 + \#199 \times \#25)_{t-n}}}$$

where N = max[1,2,3], depending on data availability;

MKTBKASS = market-to-book value of total assets, measured as:

$$\frac{\text{Market value of total assets } (\#6 - \#60 + \#199 \times \#25)_t}{\text{Book value of total assets } (\#6)_t}$$

R&D = research and development expenditure to total assets, measured as:

$$\frac{\text{Research and development expense } (\#46)_t}{\text{Book value of total assets } (\#6)_t}$$

BETA = systematic risk, estimated as the slope coefficient from a market-model regression of daily stock returns on the equally weighted NYSE, AMEX, NASD market index return over the one-year window beginning the fourth month of fiscal year *t*;

PERSIST = earnings persistence, specified as 1 when the absolute value of ΔE is above median, and 0 otherwise;

INTRATE = the mean long-term (> 10 years) composite treasury bond yield for fiscal year *t* from Standard & Poor's DRI Global Economics databank;

D_Y = 11 year-dummy variables for 1991 through 2001;

(continued on next page)

EXHIBIT 2 (continued)

D_I = 11 industry dummy variables representing two-digit SIC code numbers 13, 20, 28, 35, 36, 37, 38, 48, 50, 63, and 73;

DII = intangible intensity dummy variable, specified as 1 for observations for which nonzero values for (R&D + Advertising Expenses)-to-Capital Expenditures ratio for fiscal year t are in the top third of the distribution, and as 0 when the ratio has a value of zero and when nonzero values for (R&D + Advertising Expenses)-to-Capital Expenditures ratio are in the bottom third of the distribution. Observations in the middle third are excluded from the analysis in an effort to better distinguish between the high and low intangible-intensity sets and increase the power of tests. The (R&D + Advertising Expenses)-to-Capital Expenditures ratio is computed by dividing the sum of research and development expense (#46) and advertising expense (#45) by capital expenditures (#30) for the current year t. Missing values for research and development expense and advertising expense are coded as 0 when computing the ratio; and

$DELR$ = beginning-of-period residual liquid resources dummy variable, specified as 1 when internally available excess liquid resources at the beginning of the period are in the bottom third for the sample, and 0 when such excess liquid resources are in the top third. Observations in the middle third are excluded from the analysis in an effort to enhance the distinction between the high- and low-excess internal liquid resources sets and increase the power of tests. Excess internal liquid resources are estimated as OLS residuals from the following specification of corporate liquid resources derived from Opler et al. (1999).

$$\begin{aligned}\ln[(Cash_{t-1} + CFO_{t-1})/(Assets_{t-1} - Cash_{t-1})] = {} & a_0 + a_1 Market\text{-}to\text{-}book\text{-}ratio_{t-1} + a_2\ln(Real\_size_{t-1}) \\ & + a_3 Total\_leverage_{t-1} + a_4 Dividend\_dummy_{t-1} \\ & + a_5 Industry\_sigma_{t-1} + a_6 R\&D/Sales_{t-1} \\ & + a_7 Net\_working\_capital/Assets_{t-1} \\ & + a_8 Capital\_expenditures/Assets_{t-1} + \eta\end{aligned}$$

where:

$(Cash_{t-1} + CFO_{t-1}) / (Assets_{t-1} - Cash_{t-1})$ = a measure of the liquid resources available or anticipated at the beginning of fiscal year $t - 1$, and is defined as cash and marketable securities (#1) at the beginning of the fiscal year t plus expected CFO for fiscal year t scaled by beginning-of-year total assets (#6) excluding cash and marketable securities; where expected CFO is proxied by the realized CFO (#308) for year $t - 1$;

$Market\text{-}to\text{-}book\text{-}ratio_{t-1}$ = the same as $MKTBKASS$ (defined above) for year $t - 1$;

$Real\_size_{t-1}$ = the book value of total assets (#6) scaled by the Consumer Price Index for all Urban Consumers (Bureau of Labor Statistics 2006) both at the beginning of fiscal year t;

$Total\_leverage_{t-1}$ = the ratio of the book value of total debt (#181) to total assets at the beginning of fiscal year t;

$Dividend\_dummy_{t-1}$ = a dummy variable coded 1 when a cash dividend is paid out in the prior fiscal year $t - 1$, and 0 if no cash dividend is paid;

$Industry\_sigma_{t-1}$ = a measure of cash flow volatility in year $t - 1$ specified as the standard deviation of net income before extraordinary items (#18) less common dividends (#21) plus depreciation and amortization expense (#14) estimated for year $t - 1$ within the two-digit SIC code;

$R\&D / Sales_{t-1}$ = the research and development expense (#46) scaled by net revenues (#12), both for prior year $t - 1$;

(continued on next page)

EXHIBIT 2 (continued)

$Net\_working\_capital/Assets_{t-1}$ = the net non-cash working capital scaled by total assets, both at the beginning of year t, where non-cash working capital is defined as current assets (#4) less current liabilities (#5) less cash and marketable securities;

$Capital\_expenditures/Assets_{t-1}$ = capital expenditures (#30) in fiscal year $t-1$ scaled by total assets at the beginning of year t;

ln (.) = the natural logarithm operator; and

$a_0, \ldots, a_8$ = regression parameters and η is the error term.

---

[a] The subscript t represents the current period. Compustat data item numbers are in parentheses alongside each variable. We follow Collins and Kothari (1989) in using systematic risk (Beta) as the measure of risk, and long-term government bond-yields to proxy for risk-free interest rates.

variables appear in the specification as main effects and in interaction with current (E) and lagged earnings ($lagE$).

We define *PERSIST* as a binary measure, based on whether magnitudes of earnings changes are large (above median) or small. Freeman and Tse (1992), and Lipe et al. (1998), find that large earnings changes are less persistent than small changes. Although crude, this measure has minimal data requirements relative to time-series-based alternatives.[14]

Year and industry dummy variables help control for mean effects of remaining correlated, omitted variables. We assign dummy variables to 11 two-digit SIC code categories, each representing at least 2 percent of the sample.

Specification to Examine Relations between Investment Opportunities and CFO and Accrual Response Coefficients

We use Expression (3) to examine how CFO and accrual response coefficients vary with investment opportunities. Expression (3) follows when earnings in Expression (2′) are disaggregated into CFO and accruals:

$$\begin{aligned} CAR = {} & c_0 + c_1 IOS + c_2 IOS^2 + c_3 CFO + c_4 CFO \times IOS + c_5 CFO \times IOS^2 + c_6 lagCFO \\ & + c_7 lagCFO \times IOS + c_8 lagCFO \times IOS^2 + c_9 ACC + c_{10} ACC \times IOS + c_{11} ACC \times IOS^2 \\ & + c_{12} lagACC + c_{13} lagACC \times IOS + c_{14} lagACC \times IOS^2 + \sum_{C'} c_C \mathrm{control\_variables}_C \\ & + \sum_{Y} c_Y D_Y + \sum_{I} c_I D_I + \epsilon_c \end{aligned} \tag{3}$$

where firm and year subscripts are suppressed; variables are defined in Exhibit 2; c_0, c_1, $c_2, \ldots, c_I$ are parameter estimates; and ϵ_c is the error term.

Dechow's (1994) finding of large negative first-order serial correlations for both CFO and accruals indicates the presence of substantial mean reversion in both earnings components, and supports the use of the "current and lagged" specification to considers transitory elements in both

---

[14] We obtain similar results with Ou and Penman's (1989) binary measure of persistence based on price-earnings ratios.

CFO and accruals. Holding control variables constant, we obtain expressions for CFO and accrual response coefficients specified as $c_3 + c_4 IOS + c_5 IOS^2$ and $c_9 + c_{10} IOS + c_{11} IOS^2$, respectively, from Expression (3) above.

IV. SAMPLE SELECTION AND DESCRIPTIVE STATISTICS

Estimation of cumulative abnormal returns requires market model parameter estimates, which we obtain using prior-year data. Thus, we require daily returns from CRSP for at least two consecutive years (beginning the fourth fiscal month) during the period 1989 through 2001. We require two consecutive years of financial data on Standard & Poor's Compustat to compute current and lagged financial variables. We begin with fiscal 1990 to ensure that CFO is reported under SFAS No. 95. Following Baber et al. (1996) and Gaver and Gaver (1993), we exclude utilities (SIC 49) and banking institutions (SIC 60). Three procedures mitigate the effects of influential observations. First, we exclude observations with extreme values for *IOS* components *INVINT*, *MVAGR*, *MKTBKASS*, and *R&D*, defined as values greater than 100, 5, 30, and 1, respectively as in Baber et al. (1996). Second, we reduce outliers created by scaling with small market values of equity (MVE) by excluding observations with beginning-of-year stock price below $1.00. Third, following Easton and Harris (1991) and Cheng et al. (1996), we exclude observations for which MVE-scaled changes and levels of earnings, CFO, and accruals exceed 1.50. Our sample comprises 46,623 firm-years over fiscal years 1990–2001. Data are adjusted for stock dividends and splits.

Descriptive statistics are in Table 1, Panel A. Sample statistics for financial and market performance measures are comparable to statistics reported in other large sample studies such as Collins and Kothari (1989) and Dechow (1994), although sample firms are smaller in size. Median MVE is $141.3 million (Table 1, Panel B), substantially smaller than median MVEs of $245.3 million, $186.0 million, and $1,555.7 million reported by Collins and Kothari (1989), Ahmed (1994), and Amir and Lev (1996), respectively, even without inflation adjustment. Sample firms, although smaller than in prior studies, are larger than Compustat population firms, possibly because the two-year minimum data requirement excludes very small firms (Table 1, Panel B). Financial performance is comparable for sample firms and the Compustat population (Table 1, Panel B). Pearson and Spearman correlations (Table 1, Panel C) between CFO and accruals are substantial and negative, as in prior studies. The sample is broadly distributed across industries (Table 2).

V. RESULTS

Relations between Investment Opportunities and Earnings Response Coefficients

Table 3, Panel A, presents results for two restricted specifications of Expression (2) (Models 1 and 2) and the full specification (Model 3). Both Models 1 and 2 exclude IOS^2 and its interaction variables. Model 1, but not Model 2, restricts coefficients on current earnings (E) and its interactions to respectively equal coefficients on lagged earnings ($lagE$) and the corresponding interactions of lagged earnings. Thus, earnings changes substitute for current and lagged earnings in Expression (3) resulting in Model 1. Model 1 includes ΔE as a main effect and in interaction with *IOS*, and *BETA*, *PERSIST*, and *INTRATE*, and their interactions with ΔE appear as control variables. We present Models 1 and 2 for comparisons with Collins and Kothari (1989) and other prior studies. All models include year and industry dummy variables. We do not report coefficient estimates for control variables, and industry, and year dummies. Significance tests use Huber-White t-statistics, which are heteroscedasticity-consistent and allow for cross-sectional dependence in regression residuals within each year (Huber 1967; White 1980; Bernard 1987).

TABLE 1
Descriptive Statistics and Correlations
(Sample size n = 46,623)

Panel A: Descriptive Statistics

Variables[a]	Mean	Standard Deviation	25%	Median	75%
CAR	−0.031	0.727	−0.486	−0.180	0.198
Ret	0.140	0.768	−0.270	0.025	0.355
E	−0.004	0.187	−0.032	0.042	0.081
lagE	−0.002	0.178	−0.014	0.041	0.073
CFO	0.087	0.197	0.002	0.075	0.157
lagCFO	0.076	0.188	0.002	0.067	0.142
ACC	−0.090	0.212	−0.137	−0.046	−0.002
lagACC	−0.077	0.213	−0.114	−0.034	0.004
IOS	0.000	1.000	−0.572	−0.305	0.197
Beta	1.103	0.838	0.532	0.971	1.556
IntRate (%)	6.789	0.882	6.133	6.669	7.410

Panel B: Median Comparisons—Sample versus Compustat[a]

	MVE	Revenues	Total Assets	*E*	*CFO*	*ACC*
Our sample	141.3	154.6	149.8	0.042	0.075	−0.046
Compustat population	75.9	70.9	104.0	0.036	0.064	−0.052

(continued on next page)

TABLE 1 (continued)

Panel C: Correlations[b]

Variables[b]	***CAR***	***Ret***	***E***	***lagE***	***CFO***	***lagCFO***	***ACC***	***lagACC***	***IOS***	***Beta***	***IntRate* (%)**	***PERSIST***
CAR	—	**0.546**	**0.072**	**−0.080**	**0.127**	**0.025**	**−0.054**	**0.089**	**−0.100**	**−0.031**	**−0.049**	**0.046**
Ret	**0.616**	—	**0.189**	**−0.011**	**0.136**	**0.051**	**0.040**	**−0.054**	**−0.026**	**0.099**	**0.025**	**0.027**
E	**0.189**	**0.400**	—	**0.502**	**0.389**	**0.271**	**0.518**	**0.181**	**−0.107**	**−0.120**	**0.049**	**−0.245**
lagE	**0.051**	**0.119**	**0.554**	—	**0.211**	**0.324**	**0.245**	**0.551**	**−0.107**	**−0.124**	**0.032**	**−0.227**
CFO	**0.221**	**0.273**	**0.487**	**0.363**	—	**0.524**	**−0.586**	**−0.285**	**−0.272**	**−0.167**	**0.064**	−0.003
lagCFO	**0.135**	**0.174**	**0.381**	**0.452**	**0.576**	—	**−0.248**	**−0.611**	**−0.267**	**−0.168**	**0.066**	**−0.022**
ACC	**−0.080**	**0.027**	**0.257**	**0.089**	**−0.573**	**−0.271**	—	**0.424**	**0.159**	**0.049**	**−0.017**	**−0.212**
lagACC	**−0.109**	**−0.095**	**0.019**	**0.211**	**−0.310**	**−0.639**	**0.403**	—	**0.145**	**0.044**	**−0.031**	**−0.171**
IOS	**−0.172**	**−0.108**	**−0.204**	**−0.236**	**−0.387**	**−0.412**	**0.292**	**0.300**	—	**0.366**	**−0.092**	**−0.117**
Beta	**−0.117**	**−0.009**	**−0.156**	**−0.212**	**−0.221**	**−0.241**	**0.093**	**−0.096**	**0.384**	—	**0.022**	**0.049**
IntRate (%)	0.005	**0.098**	**0.096**	**0.063**	**0.079**	**0.080**	0.002	**−0.030**	**−0.074**	**0.044**	—	−0.001
PERSIST	**−0.009**	**−0.051**	**−0.212**	**−0.188**	**−0.032**	**−0.038**	**−0.239**	**−0.167**	**−0.173**	**0.048**	**−0.001**	—

Data are for years 1990 through 2001.

[a] In Panel A, *Ret* is the raw return for the one-year window beginning the fourth month of the fiscal year; other variables are as defined in Exhibit 2. Distribution statistics are not reported for *PERSIST* because it is a binary variable constructed with an equal number of observations in each category. In Panel B, *MVE*, *Revenues*, and *Total Assets* are in millions.

[b] Pearson (Spearman) correlations are reported above (below) the diagonal. Correlations that are significant at the 0.05 level (two-tailed) are indicated in **bold** numbers.

TABLE 2

Industry Distribution for Sample Firms

Two-Digit SIC Codes and Industry (Number of Firms)

01–09 Agricultural and Forestry (34)
10–14 Mining, including Oil and Gas Exploration (402)
15–17 Construction (116)
20–21 Food and Tobacco Products (200)
22–23 Textile and Apparel (143)
24–25 Lumber, Wood, and Furniture Products (96)
26–27 Paper, Printing, and Publishing (208)
28 Chemicals and Allied Products (633)
29 Petroleum Refining (48)
30–31 Rubber, Plastic, and Leather Products (135)
32 Stone, Clay, Glass, and Concrete Products (55)
33 Primary Metal Industries (137)
34 Fabricated Metal Industries (122)
35 Industrial and Commercial Machinery including Computing Equipment (595)
36 Electrical Machinery and Equipment (651)
37 Transportation Equipment (176)
38 Instruments (557)
39 Miscellaneous Manufacturing (101)
40–47 Transportation Services (218)
48 Communication Services (358)
50 Durable Goods—Wholesale (251)
51 Non-Durable Goods—Wholesale (124)
52–59 Retail—Various (623)
61-62 Brokerage and Credit Services (197)
63 Insurance (226)
64–67 Other Financial Services (272)
70 Hotels and Lodging Services (42)
72 Personal Services (23)
73 Business Services (1117)
75 Automobile Repair and Services (21)
76 Miscellaneous Repair Services (9)
78–79 Motion Pictures and Other Entertainment Services (165)
80–87 Health, Legal, Educational, and Consultancy Services (442)
99 Others (54)
Total = 8551

In Model 1, coefficient α_3 (1.611; $p \leq 0.01$) on ΔE indicates that the marginal ERC, holding control variables constant, is significantly positive for the average (zero *IOS*) firm and confirms a large volume of prior evidence. Coefficient α_4 (0.131; $p \leq 0.01$) on the $\Delta E \times IOS$ interaction confirms the Collins and Kothari (1989) finding that ERCs increase with investment opportunities.

TABLE 3

Regressions of Annual Cumulative Abnormal Stock Returns on Current and Lagged Earnings Conditional on the Size of the Investment Opportunity Set

(n = 46,623)

Model 1:[a] $CAR = \alpha_0 + \alpha_1 IOS + \alpha_3 \Delta E + \alpha_4 \Delta E \times IOS + \Sigma_C \alpha_C \text{control\_variables}_C + \Sigma_Y \alpha_Y D_Y + \Sigma_I \alpha_I D_I + e_\alpha$

Model 2:[a] $CAR = \beta_0 + \beta_1 IOS + \beta_5 E + \beta_6 E \times IOS + \beta_8 lagE + \beta_9 lagE \times IOS + \Sigma_C \beta_C \text{control\_variables}_C + \Sigma_Y \beta_Y D_Y + \Sigma_I \beta_I D_I + e_\beta$

Model 3:[a] $CAR = \chi_0 + \chi_1 IOS + \chi_2 IOS^2 + \chi_5 E + \chi_6 E \times IOS + \chi_7 E \times IOS^2 + \chi_8 lagE + \chi_9 lagE \times IOS + \chi_{10} lagE \times IOS^2 + \Sigma_C \chi_C \text{control\_variables}_C + \Sigma_Y \chi_Y D_Y + \Sigma_I \chi_I D_I + e_\chi$

Panel A: Coefficients

	Model 1		Model 2		Model 3	
Independent Variables/Coefficients[b]	**Coefficients**	**Huber-White t-statistics**	**Coefficients**	**Huber-White t-statistics**	**Coefficients**	**Huber-White t-statistics**
Intercept / α_0, β_0, χ_0	−0.228	−1.27	−0.228	−1.32	−0.237	−1.39
IOS / α_1, β_1, χ_1	−0.092	−9.57***	−0.102	−8.15***	−0.125	−9.96***
IOS^2 / χ_2					0.004	4.31***
ΔE / α_3	1.611	5.66***				
$\Delta E \times IOS$ / α_4	0.131	3.78***				
E / β_5, χ_5			1.537	4.19***	1.614	4.28***
$E \times IOS$ / β_6, χ_6			0.045	0.83	0.124	2.08*
$E \times IOS^2$ / χ_7					−0.053	−3.32***
$lagE$ / β_8, χ_8			−1.745	−4.08***	−1.781	−4.32***
$lagE \times IOS$ / β_9, χ_9			−0.207	−4.03***	−0.207	−5.10***
$lagE \times IOS^2$ / χ_{10}					0.006	0.30
R^2		0.0483		0.0499		0.0513

(continued on next page)

TABLE 3 (continued)

Panel B: ERCs and Rates of Change in ERCs from Model 3 at Selected *IOS* Values[c]

(1) *IOS*	(2) ERCs $(\chi_5 + \chi_6 IOS + \chi_7 IOS^2)$	(3) Huber-White t-statistics	(4) Rate of Change in ERCs $(\chi_6 + 2\chi_7 IOS)$	(5) Huber-White t-statistics
−1.0	1.437	4.22***	0.231	2.86**
0.0	1.614	4.75***	0.124	2.08*
1.0	1.684	4.89***	0.017	0.33
2.0	1.648	4.82***	−0.090	−1.46
3.0	1.504	4.63***	−0.197	−2.34**
4.0	1.254	4.35***	−0.304	−2.73**

***, **, * Indicate two-tailed significance at the 0.01, 0.05, and 0.10 levels, respectively.

[a] Variables are as defined in Exhibit 2.

[b] Coefficient estimates for control variables, and industry and year dummy variables, are not reported in the interest of parsimony and ease of exposition. These results are available from the authors.

[c] Because of the nonlinear specification of ERCs in Model 3, statistical inferences about levels and rates of changes of ERCs cannot be made directly from the model coefficients in Panel A. Therefore, in Panel B, we present estimates of ERCs and rates of changes of ERCs, along with Huber-White t-statistics, at six representative *IOS* levels (−1.0 through 4.0 at intervals of 1.0) that span the range of IOS levels in the sample. These *IOS* values represent the 0.6th percentile ($IOS = -1.0$) through the 99.0th percentile ($IOS = 4.0$) for the sample distribution. The expression for rate of change of ERC in Panel B, column (4) is the first derivative with respect to *IOS* of the expression for ERC in column (2).

The positive relation between investment opportunities and ERCs reported above is not replicated in Model 2. In Model 2, the average firm's marginal ERC (coefficient β_5 on E), is positive and significant (1.537; $p \leq 0.01$) and comparable to coefficient α_3 on ΔE in Model 1. However, the coefficient β_6 on $E \times IOS$ (0.045, $p > 0.10$), is not statistically significant. That is, while ERCs estimated by both Models 1 and 2 are similar for the average firm, ERCs increase with investment opportunities as per Model 1 but do not vary with them in Model 2. A potential explanation for this difference in slopes is that, in the presence of transitory earnings, measurement error is more substantial in ΔE, the unexpected earnings proxy in Model 1, than in the linear combination of current earnings E and lagged earnings $lagE$, which is the unexpected earnings proxy in Model 2 (Ali and Zarowin 1992; Pfeiffer and Elgers 1999). If so, then ERCs can be biased in Model 1. If the measurement error is correlated with investment opportunities, then relations between investment opportunities and ERCs can be biased. Negative, statistically significant correlations (−0.117 (Pearson), −0.173 (Spearman)) between the earnings persistence dummy (coded 1 for large, transitory earnings changes) and IOS (see Table 1, Panel B) suggest that bias may indeed exist in such relations estimated from Model 1.

The lack of significance of the coefficient on $E \times IOS$ suggests that *on average* ERCs do not increase significantly as investment opportunities increase. However, in the context of the opposing predictions of the *growth information* and *internal resource hypotheses* on the one hand and the *noisy measure hypothesis* on the other, the average result documented above may not be *representative* of the entire range of investment opportunities, or for relations with investment opportunities for CFO and accrual response coefficients. In other words, the lack of significant variation in ERCs with investment opportunities documented by Model 2 may merely reflect offsetting effects of direct and inverse relations between ERCs and investment opportunities over different parts of the investment-opportunity range and/or offsetting effects of relations between growth opportunities, and CFO and accrual response coefficients. For example, if the *internal resource hypothesis* is the primary determinant of CFO response coefficients and the *noisy measure hypothesis* largely determines accrual response coefficients, then relations with investment opportunities for the two response coefficients will diverge and may be offsetting. We provide further evidence to address these issues.

Model 3 follows Expression (2′). The expression $\chi_5 + \chi_6 IOS + \chi_7 IOS^2$, which is the coefficient of E (see Model 3 in Table 3, Panel A) indicates the marginal relation between ERCs and growth opportunities. χ_5 is the marginal ERC for the average (zero) IOS firm, χ_6 indicates the underlying linear trend in ERC with IOS, and χ_7 represents the rate of *change* in this trend.

Coefficients χ_5 and χ_6 provide direct estimates of the level and rate of change of ERCs for $IOS = 0$ only, because both levels and rates of changes in ERCs vary with IOS in Model 3. Therefore, we report ERCs levels and rates of change at six representative IOS levels of −1.0 through 4.0 at increments of 1.0 (see Table 3, Panel B). The extreme values represent the 0.6th and 99.0th percentiles of the distribution of IOS—which has mean zero and unit standard deviation by construction—and reflect its rightward skew. We estimate ERCs using the expression $\chi_5 + \chi_6 IOS + \chi_7 IOS^2$, and rates of change using its derivative, $\chi_6 + 2\chi_7 IOS$. We use the parameter variance-covariance matrix to generate test statistics and significance levels.

The increase and subsequent decline in ERCs with investment opportunities is clearly evident in the estimated values. More importantly, both the rates of increases at the lower IOS levels of −1.0 and 0.0 and the rates of declines at the higher IOS levels of 3.0 and 4.0 are statistically significant ($p < 0.05$ at $IOS = -1.0$, 3.0, and 4.0; $p < 0.10$ at $IOS = 0.0$).

Results for relations between investment opportunities and ERCs from Model 3 are summarized in column (4) of Exhibit 3, Panel A. The positive relation between investment opportunities and ERCs documented above for low IOS values indicates that the *growth information hypothesis*, or the *internal resource hypothesis*, or both predominate in explaining such relations at these levels. On the other hand, the observed negative association for high investment-opportunities firms suggests that the ***noisy measure hypothesis*** dominates at high *IOS* levels. A potential explanation for the increase in noise as investment opportunities increase lies in the increasing intangible intensity of investments as growth opportunities increase, a finding that we document later in this section (see footnote 15). As we observe in Section II, measurement error in both CFO and accruals is likely larger when investments are intangible.

Relations between CFO and Accrual Response Coefficients and Investment Opportunities

Results for Expression (3) are in Table 4, (Model 4). As in Table 3, Panel A presents parameter estimates. Panel B presents estimated CFO and accrual response coefficients, and differences between the two at selected *IOS* levels. Panel C presents rates of changes in CFO and accrual response coefficients at these *IOS* levels.

The estimated functional relationship of the CFO (accrual) response coefficient with investment opportunities is indicated by the expression $\delta_3 + \delta_4 IOS + \delta_5 IOS^2$ ($\delta_9 + \delta_{10} IOS + \delta_{11} IOS^2$). Results in Panel A show that the marginal CFO response coefficient (δ_3) and accrual response coefficient (δ_9) for the average (zero) *IOS* firm are positive and significant (1.778 ($p \leq 0.01$) and 1.241 ($p \leq 0.01$), respectively). The average *IOS* firm's accrual response coefficient is 30 percent ((1.778 − 1.241) / 1.778) smaller than the CFO response coefficient ($p \leq 0.01$). This result is in line with previous long-window studies, which typically find stronger return responses to CFO than accruals on average (Bowen et al. 1987; Ali 1994).

Relations between both CFO and accrual response coefficients, and investment opportunities are concave, as the negative and significant coefficients of $CFO \times IOS^2$ ($\delta_5 = -0.032$; $p < 0.01$) and $ACC \times IOS^2$ ($\delta_{11} = -0.034$; $p < 0.05$) indicate. The relations are plotted in Figure 1.

CFO and accrual response coefficients for selected *IOS* levels of −1.0 through 4.0 at increments of 1.0 are reported in Panel B (columns 2 and 4, respectively). All are statistically significant at the 5 percent level or better with the exception of the accrual response coefficient at $IOS = 4.0$, which is significant at the 10 percent level (see columns 3 and 5, respectively, for t-values). CFO response coefficients are significantly larger than accrual response coefficients at all reported *IOS* levels except for $IOS = 4.0$ (see columns 6 and 7) and differences increase from 26.6 percent of accrual response coefficients at $IOS = -1.0$ to 125.8 percent at $IOS = 3.0$. The lack of significance of the difference between the two response coefficients at $IOS = 4.0$, despite a larger magnitude than differences at other levels, appears to be attributable to high standard errors, potentially driven by measurement error in CFO and accruals, and/or sparse data. The larger magnitudes of CFO response coefficients relative to accrual response coefficients for much of the *IOS* range, supports hypotheses $H1_{Diff}$ and $H2_{Diff}$, and hence, both the *growth information* and *internal resource hypotheses.*

CFO response coefficients increase at statistically significant rates for *IOS* levels at and below 1.0 (see columns 2 and 3 of Table 4, Panel C). About 90 percent of the sample observations fall in this *IOS* range. Rates of change of CFO response coefficients are not statistically significant at *IOS* levels of 2.0 and higher. On the other hand, accrual response coefficients do not change significantly at *IOS* levels of 1.0 and below, but decline at significant rates ($p < 0.05$) at *IOS* levels of 2.0 and higher (see columns 4 and 5).

The finding that CFO response coefficients vary directly with investment opportunities at lower *IOS* levels supports sub-hypotheses H1C and H2C and suggests that the *growth information hypothesis* and the *internal resource hypothesis* dominate at these levels. However, the lack of association between accrual response coefficients and investment opportunities at these levels (H1A, H2A, and H3A are not supported) suggests that, for accruals, either the effects of noise (the

EXHIBIT 3
Summary of Findings[a]

Panel A: For Aggregate Sample

	Findings for Associations between Investment Opportunities and...			
(1) Hypotheses	(2) Cash Flow Response Coefficients (CRCs)	(3) Accrual Response Coefficients (ARCs)	(4) Earnings Response coefficients (ERCs)	(5) Predictions for Differences between CRCs and ARCs (CRC − ARC)
Growth information hypothesis	H1C: Positive association SUPPORTED at LOW *IOS* levels (*IOS* = −1.0, 0.0, 1.0).	H1A: Positive association NOT SUPPORTED.	H1E: Positive association SUPPORTED at LOW *IOS* levels (*IOS* = −1.0, 0.0).	$H1_{Diff}$: Positive difference SUPPORTED at ALL EXCEPT HIGHEST *IOS* (*IOS* = 4.0) level
Internal resource hypothesis	H2C: Positive association SUPPORTED at LOW *IOS* levels (*IOS* = −1.0, 0.0, 1.0).	H2A: Positive association NOT SUPPORTED.	H2E: Positive association SUPPORTED at LOW *IOS* levels (*IOS* = −1.0, 0.0).	$H2_{Diff}$: Positive difference SUPPORTED at ALL EXCEPT HIGHEST *IOS* level (i.e., except *IOS* = 4.0).
Noisy measure hypothesis	H3C: Negative association NOT SUPPORTED.	H3A: Negative association SUPPORTED at HIGH *IOS* levels (*IOS* = 2.0, 3.0, 4.0).	H3E: Negative association SUPPORTED at HIGH *IOS* levels (*IOS* = 3.0, 4.0).	No prediction
Table references for results summarized above	See Table 4, Panel C, columns (2) and(3).	See Table 4, Panel C, columns (4) and (5).	See Table 3, Panel B, columns (4) and (5).	

(continued on next page)

EXHIBIT 3 (continued)

Panel B: For Partitions by Intangible Intensity[b]

	Holding Investment-Opportunities Constant, ...	
Hypothesis	**CRCs are...**	**ARCs are...**
Internal resource hypothesis	H4C: Higher CRCs when intangible intensity is high—SUPPORTED at all *IOS* levels except extremes (*IOS* =0.0, 1.0, 2.0, 3.0).	H4A: Higher ARCs when intangible intensity is high—NOT SUPPORTED.
Noisy measure hypothesis	H5C: Lower CRCs when intangible intensity is high—NOT SUPPORTED.	H5A: Lower ARCs when intangible intensity is high—SUPPORTED at intermediate *IOS* levels ($IOS = 0.0$, 1.0).
Table references for results summarized above	See Table 5, Panel B, Sub-Panel III.	See Table 5, Panel B, Sub-Panel III.

Panel C: For Partitions by the Availability of Excess Liquid Resources[b]

	Holding Investment-Opportunities constant, ...	
Hypothesis	**CRCs are...**	**ARCs are...**
Internal resource hypothesis	H6C: higher CRCs when excess liquid resources are low—SUPPORTED for intermediate *IOS* levels (*IOS* =1.0, 2.0, 3.0).	H6A: higher ARCs when excess liquid resources are low—SUPPORTED for intermediate *IOS* ($IOS = 2.0$, 3.0).
Table references for results summarized above	See Table 6, Panel B, Sub-Panel III.	See Table 6, Panel B, Sub-Panel III.

---

[a] Because of the nonlinear specifications of CRCs, ARCs, and CRC − ARC differences, statistical inferences about levels and rates of changes of ERCs cannot be made directly from the model coefficients in Panels A of Tables 3–6. Therefore, findings are based on response coefficients estimated at six representative *IOS* levels from −1.0 through 4.0 in increments of 1.0.

[b] Intangible-intensity and excess liquid resources are defined in Exhibit 2.

TABLE 4

Regressions of Cumulative Abnormal Stock Returns on Current and Lagged Operating Cash Flows (CFO) and Accruals (ACC), Conditional on the Size of the Investment Opportunity Set (n = 46,623)

Model 4:[a] $CAR = \delta_0 + \delta_1 IOS + \delta_2 IOS^2 + \delta_3 CFO + \delta_4 CFO \times IOS + \delta_5 CFO \times IOS^2 + \delta_6 lagCFO + \delta_7 lagCFO \times IOS + \delta_8 lagCFO \times IOS^2 + \delta_9 ACC + \delta_{10} ACC \times IOS + \delta_{11} ACC \times IOS^2 + \delta_{12} lagACC + \delta_{13} lagACC \times IOS + \delta_{14} lagACC \times IOS^2 + \Sigma_C \delta_C \text{control\_variables}_C + \Sigma_Y \delta_Y D_Y + \Sigma_I \delta_I D_I + e_\delta$

Panel A: Coefficients

	Independent Variables/Coefficients[b]	Coefficients	Huber-White t-statistics
	Intercept / δ_0	−0.287	−1.72
	IOS / δ_1	−0.122	−7.44***
	IOS^2 / δ_2	0.007	3.18***
Parameters of CFO response coefficient (CRC) as a function of investment opportunities	CFO / δ_3	1.778	4.75***
	$CFO \times IOS$ / δ_4	0.232	2.73**
	$CFO \times IOS^2$ / δ_5	−0.032	−3.51***
	$lagCFO$ / δ_6	−1.926	−4.75***
	$lagCFO \times IOS$ / δ_7	−0.329	−4.34***
	$lagCFO \times IOS^2$ / δ_8	−0.007	−0.44
Parameters of accrual response coefficient (ARC) as a function of investment opportunities	ACC / δ_9	1.241	3.62***
	$ACC \times IOS$ / δ_{10}	0.011	0.28
	$ACC \times IOS^2$ / δ_{11}	−0.034	−2.46**
	$lagACC$ / δ_{12}	−1.786	−4.47***
	$lagACC \times IOS$ / δ_{13}	−0.221	−4.91***
	$lagACC \times IOS^2$ / δ_{14}	0.032	1.27
	R^2		0.0623

Panel B: CRCs and ARCs at Selected IOS Values[c]

(1) *IOS*	(2) *CRCs* ($\delta_3 + \delta_4 IOS + \delta_5 IOS^2$)	(3) Huber-White t-statistics	(4) ARCs ($\delta_9 + \delta_{10} IOS + \delta_{11} IOS^2$)	(5) Huber-White t-statistics	(6) CRCs − ARCs	(7) Huber-White t-statistics
−1.0	1.514	4.22***	1.196	3.32***	0.318	5.85***
0.0	1.778	4.75***	1.241	3.62***	0.537	9.23***
1.0	1.978	4.89***	1.218	3.70***	0.760	6.39***
2.0	2.114	4.82***	1.127	3.52***	0.987	5.07***
3.0	2.186	4.63***	0.968	3.02**	1.218	4.33***
4.0	2.194	4.35***	0.741	2.15*	1.453	1.62

(continued on next page)

TABLE 4 (continued)

Panel C: Rates of Changes in CRCs and ARCs at Selected IOS Values[c]

(1) *IOS*	(2) Rate of Change of CRCs ($\delta_4 + 2\delta_5 IOS$)	(3) Huber-White t-statistics	(4) Rate of Change of ARCs ($\delta_{10} + 2\delta_{11} IOS$)	(5) Huber-White t-statistics
−1.0	0.296	2.99**	0.079	1.39
0.0	0.232	2.73**	0.011	0.28
1.0	0.168	2.30**	−0.057	−1.46
2.0	0.104	1.62	−0.125	−2.31**
3.0	0.040	0.66	−0.193	−2.52**
4.0	−0.024	−0.42	−0.261	−2.57**

***,**,* Indicate two-tailed significance at the 0.01, 0.05, and 0.10 levels, respectively, for all individual coefficients and coefficient differences.

[a] Variables are as defined in Exhibit 2.

[b] Coefficient estimates for control variables, and industry and year dummy variables, are not reported in the interest of parsimony and ease of exposition. These results are available from the authors.

[c] Because of the nonlinear specification of CRCs and ARCs in Model 4, statistical inferences about levels and rates of changes of CRCs and ARCs cannot be made directly from the model coefficients in Panel A. Therefore, in Panel B, we present estimates for CRCs, ARCs, and CRC − ARC differences, along with Huber-White t-statistics, at six representative *IOS* levels (−1.0 through 4.0 at intervals of 1.0) that span the range of *IOS* levels in the sample. These IOS levels are the same as the levels used in Table 3, Panel B. Estimates for rates of changes of CRCs and ARCs, and related test statistics for these six *IOS* levels are presented in Table 4, Panel C. The expressions for rates of change of CRCs and ARCs in columns (2) and (4) of Panel C are obtained as the first derivatives with respect to *IOS* of the expressions for CRCs and ARCs in columns (2) and (4), respectively, of Panel B.

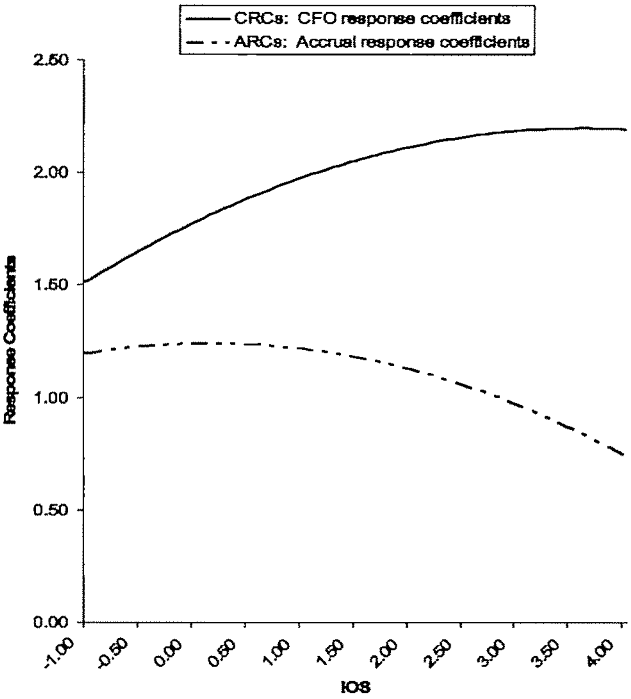
noisy measure hypothesis) offset effects of the *growth information* and *internal resource hypotheses* or that none of the three hypotheses hold.

A similar, potentially offsetting effect of measurement error in CFO appears to characterize CFO response coefficients at high *IOS* levels ($IOS = 2.0$ through $IOS = 4.0$) such that they level off and do not vary significantly with investment opportunities. On the other hand, the effect of the *noisy measure* hypothesis appears to dominate any effects of the other two hypotheses for accruals at high *IOS* levels, causing accrual response coefficients to decrease as investment opportunities increases. That is, sub-hypothesis H3A is supported at high *IOS* levels.

Results for the relations between investment opportunities and CFO and accrual response coefficients are summarized in columns (2) and (3) of Exhibit 3, Panel A. The *growth information* and/or the *internal resource hypotheses* predominate in determining relations between investment opportunities and CFO response coefficients, especially at low *IOS* levels, while the *noisy measure hypothesis* plays the primary role in relations between investment opportunities and accrual response coefficients, particularly at high *IOS* levels. Furthermore, the positive association between investment opportunities and ERCs at low *IOS* levels documented in Table 3 is driven primarily by relations between investment opportunities and CFO response coefficients. On the other hand, the

FIGURE 1

Graph of CFO Response Coefficients (CRCs) and Accrual Response Coefficients (ARCs) versus Investment Opportunities Estimated from Model 4 (Table 4)[a]



---

[a] CRCs and ARCs are estimated as in Table 4, Panel B, using the expressions $\delta_3 + \delta_4 IOS + \delta_5 IOS^2$ and $\delta_9 + \delta_{10} IOS + \delta_{11} IOS^2$, respectively. As discussed in Section III, these expressions represent the coefficients of CFO and ACC in Model 4 and estimate marginal stock return responses to unexpected CFO and accruals conditional on IOS.

negative association between investment opportunities and ERCs at high *IOS* levels is largely attributable to relations between investment opportunities and accrual response coefficients.

Tests to Distinguish among Hypotheses

Partition by the Intensity of Intangible Investments

Results for Expression (3) estimated for partitions on the intangible-intensity of investments are presented in Table 5. We measure intangible-intensity as the ratio of R&D and advertising expenditures to capital expenditures. The binary variable *DII* is coded 1 for high-intangible-intensity observations, specified as the highest third of nonzero high-intangible observations. *DII* is 0 for the lowest third or if intangible-intensity is zero. Observations in the middle third are excluded. We estimate Expression (3) for both the high and low intangible-intensity sets jointly in Model 5 (Table 5), using *DII* to distinguish the two samples. *DII* enters the model both as a main effect and in interaction with current and lagged CFO and accruals, *IOS*, and their interactions.

TABLE 5

Regressions of Cumulative Abnormal Stock Returns on Current and Lagged Operating Cash Flows (CFO) and Accruals (ACC) Conditional on Investment Opportunities and Partitioned by the Ratio of Research and Development (R&D) Plus Advertising Expenses to Capital Expenditures

(n = 36,092)

Model 5:[a] $CAR = \psi_0 + \psi_1 IOS + \psi_2 IOS^2 + \psi_3 CFO + \psi_4 CFO \times IOS + \psi_5 CFO \times IOS^2 + \psi_6 lagCFO + \psi_7 lagCFO \times IOS + \psi_8 lagCFO \times IOS^2 + \psi_9 ACC + \psi_{10} ACC \times IOS + \psi_{11} ACC \times IOS^2 + \psi_{12} lagACC + \psi_{13} lagACC \times IOS + \psi_{14} lagACC \times IOS^2 + \psi_{15} DII + \psi_{16} DII \times IOS + \psi_{17} DII \times IOS^2 + \psi_{18} DII \times CFO + \psi_{19} DII \times CFO \times IOS + \psi_{20} DII \times CFO \times IOS^2 + \psi_{21} DII \times lagCFO + \psi_{22} DII \times lagCFO \times IOS + \psi_{23} DII \times lagCFO \times IOS^2 + \psi_{24} DII \times ACC + \psi_{25} DII \times ACC \times IOS + \psi_{26} DII \times ACC \times IOS^2 + \psi_{27} DII \times lagACC + \psi_{28} DII \times lagACC \times IOS + \psi_{29} DII \times lagACC \times IOS^2 + \Sigma_C \psi_C \text{control\_variables}_C + \Sigma_Y \psi_Y D_Y + \Sigma_I \psi_I D_I + e_\psi$

Panel A: Coefficients

	(1)[b] Independent Variables/Coefficients (Coefficient Sums)[c]	(2)[b] Low R&D + Advertising Expenses-to-Capital Expenditures Ratio ($DII = 0$; n = 26,965)		(3)[b] High R&D + Advertising Expenses-to-Capital Expenditures Ratio ($DII = 1$; n = 9,127)	
		Coefficients	Huber-White t-statistics	Coefficients	Huber-White t-statistics
	Intercept / ψ_0, $\psi_0 + \psi_{15}$	−0.390	−1.90*	−0.246	−1.26
	IOS / ψ_1, $\psi_1 + \psi_{16}$	−0.188	−11.08***	−0.097	−4.26***
	IOS^2 / ψ_2, $\psi_2 + \psi_{17}$	0.020	3.16***	0.001	0.30
Parameters of CFO response coefficient (CRC) as a function of investment opportunities	CFO / ψ_3, $\psi_3 + \psi_{18}$	1.806	4.61***	2.004	4.93***
	$CFO \times IOS$ / ψ_4, $\psi_4 + \psi_{19}$	0.195	2.29**	0.404	2.18*
	$CFO \times IOS^2$ / ψ_5, $\psi_5 + \psi_{20}$	−0.087	−3.44***	−0.089	−1.72
	$lagCFO$ / ψ_6, $\psi_6 + \psi_{21}$	−1.965	−4.70***	−2.282	−5.88***
	$lagCFO \times IOS$ / ψ_7, $\psi_7 + \psi_{22}$	−0.150	−1.78	−0.310	−1.73

(continued on next page)

TABLE 5 (continued)

	(1)[b] Independent Variables/Coefficients (Coefficient Sums)[c]	(2)[b] Low R&D + Advertising Expenses-to-Capital Expenditures Ratio ($DII = 0$; n = 26,965)		(3)[b] High R&D + Advertising Expenses-to-Capital Expenditures Ratio ($DII = 1$; n = 9,127)	
		Coefficients	Huber-White t-statistics	Coefficients	Huber-White t-statistics
	$lagCFO \times IOS^2$ / ψ_8, $\psi_8 + \psi_{23}$	0.030	0.44	0.001	0.00
Parameters of accrual response coefficient (ARC) as a function of investment opportunities	ACC / ψ_9, $\psi_9 + \psi_{24}$	1.384	3.80***	1.190	3.17***
	$ACC \times IOS$ / ψ_{10}, $\psi_{10} + \psi_{25}$	0.074	1.23	−0.019	−0.20
	$ACC \times IOS^2$ / ψ_{11}, $\psi_{11} + \psi_{26}$	−0.046	−2.22**	−0.008	−0.24
	$lagACC$ / ψ_{12}, $\psi_{12} + \psi_{27}$	−1.935	−4.67***	−1.929	−4.75***
	$lagACC \times IOS$ / ψ_{13}, $\psi_{13} + \psi_{28}$	−0.181	−2.65**	−0.216	−2.22**
	$lagACC \times IOS^2$ / ψ_{14}, $\psi_{14} + \psi_{29}$	−0.010	−0.15	0.070	1.59
	R^2			0.0683	

(continued on next page)

TABLE 5 (continued)

Panel B: CRCs and ARCs at Selected *IOS* Values[d]

(1)	(2)	(3) IOS	(4) CRCs $(\psi_3 + \psi_4 IOS + \psi_5 IOS^2)$	(5) Huber-White t-statistics	(6) ARCs $(\psi_9 + \psi_{10} IOS + \psi_{11} IOS^2)$	(7) Huber-White t-statistics
Sub-Panel I	**Low Intangible-Intensity Observations ($DII = 0$)**	−1.0	1.524	4.08***	1.264	3.33***
		0.0	1.806	4.61***	1.384	3.80***
		1.0	1.915	4.52***	1.412	4.04***
		2.0	1.850	3.86***	1.349	3.79***
		3.0	1.612	2.78**	1.194	2.90**
		4.0	1.201	1.63	0.948	1.78
		IOS	**CRCs** $((\psi_3 + \psi_{18}) + (\psi_4 + \psi_{19})IOS + (\psi_5 + \psi_{20})IOS^2)$	**Huber-White t-statistics**	**ARCs** $((\psi_9 + \psi_{24}) + (\psi_{10} + \psi_{25})IOS + (\psi_{11} + \psi_{26})IOS^2)$	**Huber-White t-statistics**
Sub-Panel II	**High Intangible-Intensity Observations ($DII = 1$)**	−1.0	1.510	3.40***	1.200	2.81**
		0.0	2.004	4.93***	1.190	3.17***
		1.0	2.318	5.18***	1.163	3.26***
		2.0	2.454	5.19***	1.119	3.22***
		3.0	2.411	5.10***	1.059	2.95**
		4.0	2.189	4.37***	0.981	2.25**

(continued on next page)

TABLE 5 (continued)

		IOS	CRCs difference ($\psi_{18} + \psi_{19}IOS + \psi_{20}IOS^2$)	Huber-White t-statistics	ARCs difference ($\psi_{24} + \psi_{25}IOS + \psi_{26}IOS^2$)	Huber-White t-statistics
Sub-Panel III	**Difference High minus low Intangible-intensity Observations**	−1.0	−0.014	−0.10	−0.064	−0.48
		0.0	0.198	2.58**	−0.194	−2.03*
		1.0	0.404	3.41***	−0.249	−1.85*
		2.0	0.604	4.41***	−0.230	−1.11
		3.0	0.799	2.77**	−0.136	−0.36
		4.0	0.988	1.62	0.033	0.00

***,**,* Indicate two-tailed significance at the 0.01, 0.05, and 0.10 levels, respectively, for all individual coefficients and coefficient differences.

[a] Variables are defined in Exhibit 2.

[b] Model 5 is estimated as a single specification combining both low and high R&D + Advertising-to-Capital-Expenditures ratio observations. However, for ease of exposition, results are reported separately for observations with low and high values for the ratio in columns (2) and (3) respectively, of Panel A. These coefficients are computed by substituting $DII = 0$ and $DII = 1$, respectively in the estimated Model 5.

When $DII = 0$, Model 5 reduces to the following expression:

$$CAR = \psi_0 + \psi_1 IOS + \psi_2 IOS^2 + \psi_3 CFO + \psi_4 CFO \times IOS + \psi_5 CFO \times IOS^2 + \psi_6 lagCFO + \psi_7 lagCFO \times IOS + \psi_8 lagCFO \times IOS^2 + \psi_9 ACC + \psi_{10} ACC \times IOS + \psi_{11} ACC \times IOS^2 + \psi_{12} lagACC + \psi_{13} lagACC \times IOS + \psi_{14} lagACC \times IOS^2 + \Sigma_C \psi_C \text{control\_variable}_C + \Sigma_Y \psi_Y D_Y + \Sigma_I \psi_I D_I + e_\psi$$

Results for this expression are in column (2) of Panel A.

When $DII = 1$, Model 5 reduces to the following expression:

$$CAR = (\psi_0 + \psi_{15}) + (\psi_1 + \psi_{16})IOS + (\psi_2 + \psi_{17})IOS^2 + (\psi_3 + \psi_{18})CFO + (\psi_4 + \psi_{19})CFO \times IOS + (\psi_5 + \psi_{20})CFO \times IOS^2 + (\psi_6 + \psi_{21})lagCFO + (\psi_7 + \psi_{22})lagCFO \times IOS + (\psi_8 + \psi_{23})lagCFO \times IOS^2 + (\psi_9 + \psi_{24})ACC + (\psi_{10} + \psi_{25})ACC \times IOS + (\psi_{11} + \psi_{26})ACC \times IOS^2 + (\psi_{12} + \psi_{27})lagACC + (\psi_{13} + \psi_{28})lagACC \times IOS + (\psi_{14} + \psi_{29})lagACC \times IOS^2 + \Sigma_C \psi_C \text{control\_variable}_C + \Sigma_Y \psi_Y D_Y + \Sigma_I \psi_I D_I + e_\psi$$

Results for this expression are in column (3) of Panel A.

Column (1) of Panel A indicates the coefficient symbol (coefficient sum expression) for each independent variable for the low (high) ratio sample. For example, ψ_0, $(\psi_0 + \psi_{15})$ represents the coefficient (coefficient sum) that represents the estimated intercept for the low (high) ratio sample.

[c] Coefficient estimates for control variables, and industry and year dummy variables, are not reported in the interest of parsimony and ease of exposition. These results are available from the authors.

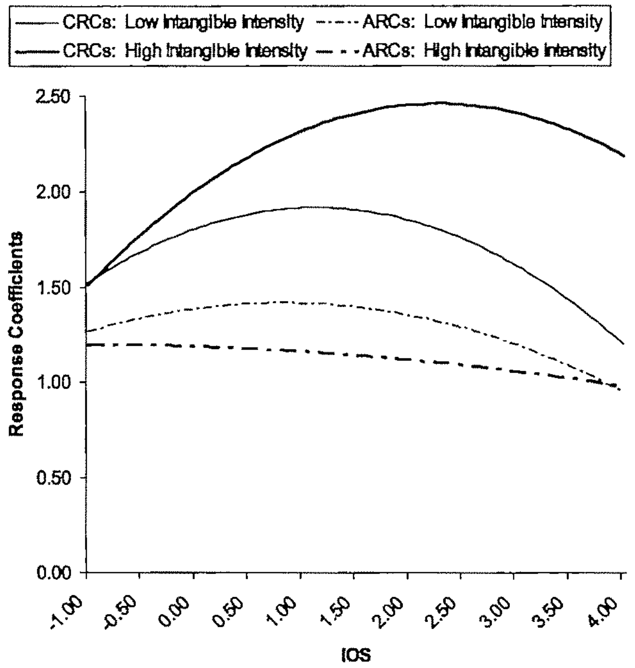
[d] Because of the nonlinear specification of CRCs and ARCs in Model 5, statistical inferences about levels and rates of changes of CRCs and ARCs cannot be made directly from the model coefficients in Panel A. Therefore, in Panel B, we present estimates for CRCs, and ARCs (in Sub-Panels I and II), and CRC-ARC differences (in Sub-Panel III), along with Huber-White t-statistics, at six representative *IOS* levels (−1.0 through 4.0 at intervals of 1.0) that span the range of *IOS* levels in the sample. These *IOS* levels are the same as in Table 3, Panel B.

Model parameters are reported in Table 5, Panel A. Note that Model 5 reduces to Expression (3) for low (high) intangible-intensity observations when $DII = 0$ ($DII = 1$). Coefficient estimates are reported in columns (2) and (3) of Table 5, Panel A, for low and high intangible-intensity observations respectively, and are based on these substitutions for DII. Reduced specifications obtained through such substitutions are shown in footnote b of Table 5.

Interpretations of coefficients are as in Table 4. Estimated CFO (accrual) response coefficients as functions of IOS are indicated by the expression $\psi_3 + \psi_4 IOS + \psi_5 IOS^2$ $(\psi_9 + \psi_{10} IOS + \psi_{11} IOS^2)$ for low intangible-intensity observations ($DII = 0$). Substituting $DII = 1$ for high intangible-intensity observations in Model 5 in Table 5 yields $(\psi_3 + \psi_{18}) + (\psi_4 + \psi_{19}) IOS + (\psi_5 + \psi_{20}) IOS^2$ $[(\psi_9 + \psi_{24}) + (\psi_{10} + \psi_{25}) IOS + (\psi_{11} + \psi_{26}) IOS^2]$ as the expression for CFO [accrual] response coefficients. Figure 2 provides a graphical representation of relations between investment

FIGURE 2

Graph of CFO Response Coefficients (CRCs) and Accrual Response Coefficients (ARCs) versus Investment Opportunities Estimated from Model 5 (Table 5) for High and Low Intangible-Intensity Firm-Years[a]



---

[a] CRCs (ARCs) are estimated as in Table 5, Panel B. CRCs [ARCs] for low intangible-intensity observations are estimated using the expression $\psi_3 + \psi_4 IOS + \psi_5 IOS^2$ $[\psi_9 + \psi_{10} IOS + \psi_{11} IOS^2]$ and for high intangible-intensity observations using the expression $(\psi_3 + \psi_{18}) + (\psi_4 + \psi_{19}) IOS + (\psi_5 + \psi_{20}) IOS^2 [(\psi_9 + \psi_{24}) + (\psi_{10} + \psi_{25}) IOS + (\psi_{11} + \psi_{26}) IOS^2]$. As discussed in Section III, these expressions represent coefficients of CFO and ACC in Model 5 for low and high intangible-intensity observations, respectively, and estimate marginal stock return responses to unexpected CFO and accruals conditional on IOS and intangible intensity of investments.

opportunities and CFO and accrual response coefficients for high and low intangible-intensity observations.

Figure 2 suggests that CFO response coefficients for both high and low intangible-intensity firms are comparable at low *IOS* levels, but CFO response coefficients for high intangible-intensity firms increase more rapidly and remain at higher levels than those for low intangible-intensity firms except at very high *IOS* levels. Accrual response coefficients for high intangible-intensity firms are substantially lower than those for low intangible-intensity firms at intermediate *IOS* levels but not at the extremes. These observations are supported by the statistical evidence in Panels B of Table 5. Table 5, Panel B reports estimated CFO response coefficients (column (4)) and accrual response coefficients (column (6)) for low and high intangible-intensity observations for *IOS* values ranging from -1.0 through 4.0 in Sub-Panels I and II, respectively. Sub-Panel III reports differences in CFO response coefficients and accrual response coefficients between the high and low intangible-intensity observation sets. Huber-White t-statistics are reported to the right of the estimated response coefficients in columns (5) and (7) respectively.

Evidence in Sub-Panels I and II of Table 5, Panel B is consistent with Panel B of Table 4. CFO and accrual response coefficients are positive and significant at all reported *IOS* levels for both low and high intangible-intensity observations, with the exception of $IOS = 4.0$ for low intangible-intensity firms.

Sub-Panel III of Table 5, Panel B shows that CFO response coefficients are significantly higher ($p < 0.05$ or better) for high intangible-intensity observations for intermediate *IOS* levels of 0.0 through 3.0, but not at the extreme *IOS* levels of -1.0 and 4.0. At $IOS = -1.0$, the difference in CFO response coefficients ($1.510 - 1.524 = -0.014$) is neither material (($0.014 / 1.524 = 0.9$ percent of CFO response coefficients for low intangible-intensity observations) nor significant. At $IOS = 4.0$, the difference is larger in magnitude than at other *IOS* levels (the high intangible-intensity CFO response coefficient is 82 percent ($0.988 / 1.201$) larger than the low intangible-intensity CFO response coefficient) but not statistically significant, likely because of larger standard errors. In sum, over a substantial range of *IOS* levels, CFO response coefficients for high intangible-intensity observations significantly exceed those for low intangible-intensity observations. Moreover, these differences are also material in magnitude, ranging from 11 percent ($0.198 / 1.806$) of low intangible-intensity CFO response coefficients at $IOS = 0.0$ to almost 50 percent ($0.799 / 1.612$) at $IOS = 3.0$. These results are consistent with the *internal resource hypothesis* as embodied in sub-hypothesis H4C. They do not support sub-hypothesis H5C of the *noisy measure hypothesis*, and indicate that the effect of measurement error in CFO is not a dominant factor in determining *differences* between high versus low intangible-intensity firms in CFO response coefficients..

Comparisons in Sub-Panel III of Table 5, Panel B show that accrual response coefficients for high intangible-intensity observations are significantly lower than those for low intangible-intensity observations at intermediate reported *IOS* levels of 0.0 and 1.0. Differences are not significant at other reported *IOS* levels. These results suggest that the effect of measurement error in accruals on relations between investment opportunities and accrual response coefficients is more substantial for high intangible-intensity observations, at least at intermediate *IOS* levels. Thus, the *noisy measure hypothesis* dominates in determining accrual response coefficient differences between high and low intangible-intensity observations, supporting sub-hypothesis H5A. In sum, these results clearly support both the *internal resource hypothesis* with regard to CFO response coefficients and the *noisy measure hypothesis* with regard to accrual response coefficients. Results are summarized in Exhibit 3, Panel B.

A concern with the above analysis is that R&D expense is a component of both the investment opportunities measure (*IOS*) and the intangible-intensity measure (*DII*) which is the partitioning variable. If correlations between *IOS* and *DII* are substantial, then partitioning on intangible-intensity can result in large differences across the partitions on *IOS* as well. If so, then differences in CFO and accrual response coefficients attributed to differences in intangible-intensity may merely reflect differences in *IOS*. Thus, we repeat the above analysis using a second investment opportunities measure (*IOS2*) that is the first principal component of the two *IOS* constituents *MKTBKASS* (market-to-book ratio of assets) and *MVAGR* (asset growth rate), which do not include R&D expense. We retain *DII* as the intangible-intensity partitioning variable. Results are qualitatively similar to those using *IOS*.[15] Thus, results reported in Table 5 do not appear to be driven by differences in investment opportunities across the intangible-intensity partitions.

Partition by the Availability of Excess Liquid Resources

Table 6 presents results for Expression (3) partitioned by the extent that liquid resources are available to meet investment needs. We use Opler et al.'s (1999) model of corporate holdings of liquid assets to develop a measure of excess liquid resources. Opler et al. (1999) model liquid asset holdings—cash and marketable securities—at the beginning of a fiscal period as a function of operating and investment needs for the period, including capital expenditures, growth opportunities, working capital, and business and financial risk. We modify Opler et al.'s (1999) measure by adding expected CFO for the period. Thus, we derive a more comprehensive measure of beginning-period liquid resources that encompasses both liquid resources on hand and expected during the current year. We use prior period actual CFO to proxy for expected CFO for the current year, thus assuming a parsimonious random-walk characterization for the CFO time-series process.[16] We specify the residuals from the re-estimation of the Opler et al. (1999) model using the modified liquid holdings measures, as the measure of excess liquid resources. Exhibit 2 describes the specification used to estimate residual excess liquid resources (see the definition of the dummy variable *DELR*).

We partition the sample into three groups by rank order of the residuals. We specify a binary variable *DELR*, coded 0 for the largest (most positive) residuals, and 1 for the smallest residuals. The middle third is excluded from the sample. Thus, observations with *DELR* coded 1 are the most liquidity-constrained and those with *DELR* coded 0 are the least constrained.[17]

Results reported in Table 6 are estimated using the full specification of Model 6. Model 6 is similar to Model 5 (Table 5) except that *DELR* replaces *DII*. As in Table 5, model parameters are presented in separate columns in Table 6, Panel A for the low ($DELR = 1$ in column (3)) and high ($DELR = 0$ in column (2)) excess liquid resource observations. Interpretations of coefficients and CFO and accrual response coefficient functions are as in Table 5. Figure 3 graphs relations between investment opportunities and CFO and accrual response coefficients for the two sets of observations.

---

[15] Pearson (Spearman) correlations between *IOS2* and *DII* are only 0.146 (0.070), and considerably lower than correlations of 0.463 (0.448) between *IOS* and *DII*. Thus, concerns that partitioning on *DII* leads to spurious partitioning on investment opportunities should be mitigated.

[16] Results are insensitive to excluding expected current period CFO from the liquid resource measure. Results are also similar when the raw liquid resource balance (beginning-of-year cash and marketable securities) or raw available and anticipated liquid resources (beginning-of-year cash and marketable securities plus prior year CFO) are used instead of residuals from the Opler et al. (1999) model to partition the sample on internal liquid resources. Results are robust to the substitution of *IOS* as the growth measure in the Opler et al. (1999) model instead of the market-to-book ratio and the R&D expense-to-sales ratio. Finally, results are also similar when the two measures of growth opportunities are entirely excluded from the Opler et al. (1999) model in estimating excess internal liquid resources.

[17] Correlations between the intangible-intensity dummy variable *DII* and the excess internal liquid resources dummy variable *DELR* are relatively low at −0.149. Thus, partitions on these two variables appear to be relatively orthogonal.

TABLE 6

Regressions of Cumulative Abnormal Stock Returns on Current and Lagged Operating Cash Flows (CFO) and Accruals (ACC) Conditional on Investment Opportunities and Partitioned by the Beginning of Period Excess Liquid Resources

(n = 30,349)

Model 6:[a] $CAR = \kappa_0 + \kappa_1 IOS + \kappa_2 IOS^2 + \kappa_3 CFO + \kappa_4 CFO \times IOS + \kappa_5 CFO \times IOS^2 + \kappa_6 lagCFO + \kappa_7 lagCFO \times IOS + \kappa_8 lagCFO \times IOS^2 + \kappa_9 ACC + \kappa_{10} ACC \times IOS + \kappa_{11} ACC \times IOS^2 + \kappa_{12} lagACC + \kappa_{13} lagACC \times IOS + \kappa_{14} lagACC \times IOS^2 + \kappa_{15} DELR + \kappa_{16} DELR \times IOS + \kappa_{17} DELR \times IOS^2 + \kappa_{18} DELR \times \mathrm{CFO} + \kappa_{19} DELR \times \mathrm{CFO} \times IOS + \kappa_{20} DELR \times \mathrm{CFO} \times IOS^2 + \kappa_{21} DELR \times \mathrm{lagCFO} + \kappa_{22} DELR \times \mathrm{lagCFO} \times IOS + \kappa_{23} DELR \times \mathrm{lagCFO} \times IOS^2 + \kappa_{24} DELR \times ACC + \kappa_{25} DELR \times ACC \times IOS + \kappa_{26} DELR \times ACC \times IOS^2 + \kappa_{27} DELR \times lagACC + \kappa_{28} DELR \times lagACC \times IOS + \kappa_{29} DELR \times lagACC \times IOS^2 + \Sigma_C \kappa_C control\_variables_C + \Sigma_Y \kappa_Y D_Y + \Sigma_I \kappa_I D_I + e_\kappa$

Panel A: Coefficients

	(1) Independent Variables/Coefficients[c]	(2)[b] High Excess Liquid Resources ($DELR$ = 0; n = 15,174)		(3)[b] Low Excess Liquid Resources ($DELR$ = 1; n = 15,175)	
		Coefficients	Huber-White t-statistics	Coefficients	Huber-White t-statistics
	Intercept / κ_0, $\kappa_0 + \kappa_{15}$	−0.395	−2.37**	−0.365	−1.99**
	IOS / κ_1, $\kappa_1 + \kappa_{16}$	−0.110	−5.75***	−0.139	−6.03***
	IOS^2 / κ_2, $\kappa_2 + \kappa_{17}$	0.004	1.21	0.009	1.66
Parameters of CFO response coefficient (CRC) as a function of investment opportunities	CFO / κ_3, $\kappa_3 + \kappa_{18}$	2.104	4.24***	2.163	4.51***
	$CFO \times IOS$ / κ_4, $\kappa_4 + \kappa_{19}$	0.036	0.37	0.384	3.21***
	$CFO \times IOS^2$ / κ_5, $\kappa_5 + \kappa_{20}$	−0.035	−0.90	−0.039	−1.47
	$lagCFO$ / κ_6, $\kappa_6 + \kappa_{21}$	−2.279	−10.14***	−2.018	−7.47***
	$lagCFO \times IOS$ / κ_7, $\kappa_7 + \kappa_{22}$	−0.471	−4.13***	−0.372	−3.09**

(continued on next page)

TABLE 6 (continued)

	(1) Independent Variables/Coefficients[c]	(2)[b] High Excess Liquid Resources ($DELR = 0$; n = 15,174)		(3)[b] Low Excess Liquid Resources ($DELR = 1$; n = 15,175)	
		Coefficients	Huber-White t-statistics	Coefficients	Huber-White t-statistics
	$lagCFO \times IOS^2 / \kappa_8,\ \kappa_8 + \kappa_{23}$	0.024	0.66	−0.040	−1.21
Parameters of accrual response coefficient (ARC) as a function of investment opportunities	$ACC / \kappa_9,\ \kappa_9 + \kappa_{24}$	1.697	3.69***	1.668	3.62***
	$ACC \times IOS / \kappa_{10},\ \kappa_{10} + \kappa_{25}$	−0.098	−1.74	0.166	2.43**
	$ACC \times IOS^2 / \kappa_{11},\ \kappa_{11} + \kappa_{26}$	−0.037	−1.31	−0.043	−0.95
	$lagACC / \kappa_{12},\ \kappa_{12} + \kappa_{27}$	−2.071	−8.27***	−1.833	−7.26***
	$lagACC \times IOS / \kappa_{13},\ \kappa_{13} + \kappa_{28}$	−0.282	−4.17***	−0.040	−0.35
	$lagACC \times IOS^2 / \kappa_{14},\ \kappa_{14} + \kappa_{29}$	0.059	2.68***	0.004	0.10
	R^2	0.0647			

(continued on next page)

TABLE 6 (continued)

Panel B: CRCs and ARCs at Selected IOS Values[d]

(1)	(2)	(3) IOS	(4) CRCs $(\kappa_3 + \kappa_4 IOS + \kappa_5 IOS^2)$	(5) Huber-White t-statistics	(6) ARCs $(\kappa_9 + \kappa_{10} IOS + \kappa_{11} IOS^2)$	(7) Huber-White t-statistics
Sub-Panel I	**High excess liquid resource observations (*DELR* = 0)**	−1.0	2.033	4.53***	1.758	3.77***
		0.0	2.104	4.24***	1.697	3.69***
		1.0	2.105	3.79***	1.562	3.44***
		2.0	2.035	3.25***	1.353	2.94**
		3.0	1.894	2.59**	1.068	2.10*
		4.0	1.682	1.86*	0.710	1.13
		IOS	CRCs $((\kappa_3 + \kappa_{18}) + (\kappa_4 + \kappa_{19}) IOS + (\kappa_5 + \kappa_{20}) IOS^2)$	Huber-White t-statistics	ARCs $((\kappa_9 + \kappa_{24}) + (\kappa_{10} + \kappa_{25}) IOS + (\kappa_{11} + \kappa_{26}) IOS^2)$	Huber-White t-statistics
Sub-Panel II	**Low excess liquid resource observations (*DELR* = 1)**	−1.0	1.741	3.43***	1.459	3.02**
		0.0	2.163	4.51***	1.668	3.62***
		1.0	2.508	5.16***	1.791	4.06***
		2.0	2.776	5.46***	1.830	4.38***
		3.0	2.966	5.51***	1.783	4.03***
		4.0	3.080	5.25***	1.652	2.80**

(continued on next page)

TABLE 6 (continued)

		IOS	CRC difference ($\kappa_{18} + \kappa_{19}IOS + \kappa_{20}IOS^2$)	Huber-White t-statistics	ARC difference ($\kappa_{24} + \kappa_{25}IOS + \kappa_{26}IOS^2$)	Huber-White t-statistics
Sub-Panel III	**Difference: Low minus high excess liquid resources observations**	−1.0	−0.292	−3.02**	−0.299	−3.63***
		0.0	0.059	0.52	0.030	0.28
		1.0	0.403	2.21*	0.229	1.66
		2.0	0.741	2.60**	0.477	2.85**
		3.0	1.073	2.24**	0.715	2.07*
		4.0	1.397	1.78	0.942	1.39

***, **, * Indicate two-tailed significance at the 0.01, 0.05, and 0.10 levels, respectively, for all individual coefficients and coefficient differences.

[a] Variables are defined in Exhibit 2.

[b] Model 6 is estimated as a single specification combining both high and low excess liquid resources observations. For ease of exposition, results are reported separately for observations with high and low values for the ratio in columns (2) and (3), respectively. These coefficients are computed by substituting $DELR = 0$ and $DELR = 1$, respectively, in the estimated Model 6.

When $DELR = 0$, Model 6 reduces to the following expression:

$$CAR = \kappa_0 + \kappa_1 IOS + \kappa_2 IOS^2 + \kappa_3 CFO + \kappa_4 CFO \times IOS + \kappa_5 CFO \times IOS^2 + \kappa_6 lagCFO + \kappa_7 lagCFO \times IOS + \kappa_8 lagCFO \times IOS^2 + \kappa_9 ACC + \kappa_{10} ACC \times IOS + \kappa_{11} ACC \times IOS^2 + \kappa_{12} lagACC + \kappa_{13} lagACC \times IOS + \kappa_{14} lagACC \times IOS^2 + \Sigma_C \kappa_C \text{control\_variable}_C + \Sigma_Y \kappa_Y D_Y + \Sigma_I \kappa_I D_I + e_\kappa$$

Results for this expression are in column (2) of Panel A.

When $DELR = 1$, Model 6 reduces to the following expression:

$$CAR = (\kappa_0 + \kappa_{15}) + (\kappa_1 + \kappa_{16}) IOS + (\kappa_2 + \kappa_{17}) IOS^2 + (\kappa_3 + \kappa_{18}) CFO + (\kappa_4 + \kappa_{19}) CFO \times IOS + (\kappa_5 + \kappa_{20}) CFO \times IOS^2 + (\kappa_6 + \kappa_{21}) lagCFO + (\kappa_7 + \kappa_{22}) lagCFO \times IOS + (\kappa_8 + \kappa_{23}) lagCFO \times IOS^2 + (\kappa_9 + \kappa_{24}) ACC + (\kappa_{10} + \kappa_{25}) ACC \times IOS + (\kappa_{11} + \kappa_{26}) ACC \times IOS^2 + (\kappa_{12} + \kappa_{27}) lagACC + (\kappa_{13} + \kappa_{28}) lagACC \times IOS + (\kappa_{14} + \kappa_{29}) lagACC \times IOS^2 + \Sigma_C \kappa_C \text{control\_variable}_C + \Sigma_Y \kappa_Y D_Y + \Sigma_I \kappa_I D_I + e_\kappa$$

Results for this expression are in column (3) of Panel A.

Column (1) of Panel A indicates the coefficient symbol (coefficient sum expression) for each independent variable for the high (low) excess liquid resources sample. For example, κ_0, $(\kappa_0 + \kappa_{15})$ represents the coefficient (coefficient sum) that represents the estimated intercept for the high (low) excess liquid resources sample.

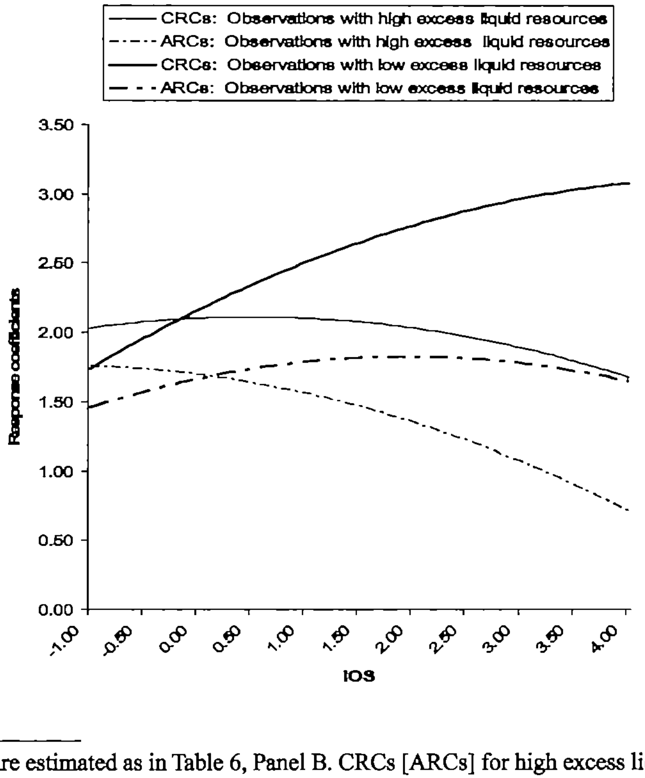
[c] Coefficient estimates for control variables, and industry and year dummy variables, are not reported in the interest of parsimony and ease of exposition. These results are available from the authors.

[d] Because of the nonlinear specification of CRCs and ARCs in Model 6, statistical inferences about levels and rates of changes of CRCs and ARCs cannot be made directly from the model coefficients in Panel A. Therefore, in Panel B, we present estimates for CRCs, and ARCs (in Sub-Panels I and II), and CRC-ARC differences (in Sub-Panel III), along with Huber-White t-statistics, at six representative IOS levels (−1.0 through 4.0 at intervals of 1.0) that span the range of IOS levels in the sample. These IOS levels are the same as the levels used in Table 3, Panel B.

Figure 3 shows that CFO response coefficients for firms with low excess liquid resources begin below those for high excess liquid resources at low *IOS* levels, but surpass them at average *IOS* levels, and remain greater than high excess liquid resources CFO response coefficients at high *IOS* levels. A similar pattern is observed for comparisons of accrual response coefficients for low and high excess liquid resources firms. Table 6, Panel B provides statistical comparisons to complement the observations from Figure 3. Estimated CFO and accrual response coefficients are reported in Table 6, Panel B for both high and low excess liquid resources observations for *IOS* levels of −1.0 through 4.0 at 1.0 intervals. CFO response coefficients are positive and statistically significant at all six *IOS* levels, increasing from 1.741 to 3.080 for the low excess liquid resources observations (see Sub-Panel II, column 4) and declining from 2.033 to 1.682 for the high excess

FIGURE 3

Graph of CFO Response Coefficients (CRCs) and Accrual Response Coefficients (ARCs) versus Investment Opportunities Estimated from Model 6 (Table 6) for Firms with High and Low Excess Liquid Resources [a]



---

[a] CRCs and ARCs are estimated as in Table 6, Panel B. CRCs [ARCs] for high excess liquid resources observations are estimated using the expression $\kappa_3 + \kappa_4 IOS + \kappa_5 IOS^2$ [$\kappa_9 + \kappa_{10} IOS + \kappa_{11} IOS^2$] and for low excess liquid resources observations using the Expression $(\kappa_3 + \kappa_{18}) + (\kappa_4 + \kappa_{19})\ IOS + (\kappa_5 + \kappa_{20}) IOS^2$ [$(\kappa_9 + \kappa_{24}) + (\kappa_{10} + \kappa_{25}) IOS + (\kappa_{11} + \kappa_{26}) IOS^2$]. As discussed in Section III, these expressions represent coefficients of CFO and ACC in Model 6 for high and low excess liquid resources observations respectively and estimate marginal stock return responses to unexpected CFO and accruals conditional on *IOS* and the availability of liquid resources.

liquid resources observations (see Sub-Panel I, column 4). More importantly, at high *IOS* levels (*IOS* = 1.0, 2.0, and 3.0), CFO response coefficients are significantly higher for firms with few liquid resources than those with abundant liquid resources (see Sub-Panel III, column 4), with differences ranging from 19 percent (0.403 / 2.105) to 57 percent (1.073 / 1.894) of the CFO response coefficients for high excess liquid resources observations. That is, for firms with substantial investment opportunities, the unexpected availability of CFO has a more positive impact on equity value when the firms are cash-constrained than when they are not. This result is consistent with sub-hypothesis H6C of the *internal resource hypothesis*. The CFO-response-coefficient difference at the highest *IOS* level (*IOS* = 4.0) is larger than at other levels (1.397 / 1.682 = 83 percent) but is not statistically significant due to high standard errors.

Similar assessments of accrual response coefficients can be made from column 6 of Table 6, Panel B. Accrual response coefficients decline monotonically with investment opportunities over the reported *IOS* levels for high excess liquid resources observations (see Sub-Panel I), but increase and then decline for low excess liquid resources observations (see Sub-Panel II). Comparisons of accrual response coefficients between the two excess liquid resources levels show that at the relatively high *IOS* levels of *IOS* = 2.0 and *IOS* = 3.0, these response coefficients are higher for more liquidity-constrained firms than for less liquidity-constrained firms. This is consistent with sub-hypothesis H6A of the *internal resource hypothesis*. As with CFO response coefficient differences, accrual response coefficient differences, although substantial in magnitude are not statistically significant at *IOS* = 4.0. A summary of results is in Exhibit 3, Panel C.

Both CFO and accrual response coefficients are significantly lower for low excess liquid resources firms than for high excess liquid resources firms at the lowest *IOS* level (*IOS* = –1.0). At this level, there are few growth opportunities available to be realized by using unexpected CFO. On the other hand, at these *IOS* levels, low excess liquid resources levels may signal financial distress and indicate that unexpected CFO (and accruals) are likely to be transitory.

Finally, agency costs can be high when excess liquid resources are substantial because of concerns that such resources may be expropriated or deployed unproductively (Jensen 1986). Moreover, agency costs potentially increase with investment opportunities. Thus, high agency costs can reduce the credibility of financial information and may also contribute to lower response coefficients for high excess liquid resources observations at high investment-opportunity levels.

Sensitivity Analyses

We perform additional tests to examine the robustness of our findings to alternative explanations. Hayn (1995) finds that losses are less value-relevant than profits. Freeman and Tse (1992) find that large earnings changes are transitory and have lower ERCs. If the incidence of losses or large earnings changes is correlated with investment opportunities, then our findings may be attributable to these factors rather than the size of the investment opportunity set.[18] We find that conclusions are similar, both when we re-estimate all models after excluding loss firm-years and when we re-estimate them after excluding large earnings-change observations from the sample. We define earnings changes as large when they are above the median for the sample.

---

[18] Correlations between *IOS* and *LOSS*, a dummy variable coded 1 for loss firm-years, and 0 otherwise, are positive and significant (Pearson: 0.22 ($p \leq 0.01$); Spearman: 0.12 ($p \leq 0.01$)). Correlations between *IOS* and *PERSIST*, a dummy variable coded 1 for large—above median—earnings changes, and 0 otherwise, are negative and significant (Pearson: −0.12 ($p \leq 0.01$); Spearman: −0.17 ($p \leq 0.01$)) (see Table 1, Panel B). These associations indicate the need for the sensitivity analysis that is reported here.

Dechow (1994) finds that differences in the value-relevance of earnings and CFO are associated with the magnitude of accruals and the length of the operating and trade cycles. Results are similar when we include each variable in turn as additional main and interaction variables in the specifications.

We also consider alternative specifications of abnormal returns. Specifically, we use return windows that match the fiscal year and abnormal returns specified as risk-adjusted returns relative to the value-weighted market index, market-adjusted returns, and raw returns. Results are robust to these variations.

Finally, in order to address concerns that findings about the relations between investment opportunities and earnings, CFO and accrual response coefficients may be artifacts of the quadratic specifications, we consider piece-wise linear specifications. Results are similar.

VI. SUMMARY AND CONCLUSIONS

We examine how the value-relevance of earnings and its components—CFO and accruals—vary with investment opportunities. Existing evidence about relations between earnings value-relevance and investment opportunities is mixed, and we are unaware of research that considers how the value-relevance of earnings components vary with investment opportunities.

We find that ERCs first increase and then decline as investment opportunities increase. CFO response coefficients also increase with investment opportunities at low investment-opportunity levels, but level off when investment opportunities are high. Accrual response coefficients, on the other hand, vary inversely with investment opportunities at high investment-opportunity levels. Furthermore, for most investment-opportunity levels, CFO response coefficients are larger and increase at a faster rate than accrual response coefficients. The inverse variation of accrual response coefficients with investment opportunities at high investment-opportunity levels is consistent with the premise that deficiencies in accounting measurement cause accruals to decline in value-relevance for high-growth firms.

The positive slope of the relations between investment opportunities, and ERCs and CFO response coefficients at low growth-opportunity levels, and the larger magnitude of the latter relative to the slope of relations between investment opportunities and accrual response coefficients are consistent with two explanations. The first is that investors learn from current earnings surprises about the earnings potential of future growth opportunities. The second explanation is that cost differentials between internal and external financing cause CFO to be an increasingly important determinant of value as investment opportunities increase.

We perform tests using two different partitioning schemes to distinguish between these explanations. The first splits the sample on the extent that investments are in intangible assets. We find that at intermediate investment-opportunity levels, CFO response coefficients are higher and accrual response coefficients lower when investments are substantially in intangible assets. Higher CFO response coefficients are consistent with the explanation that greater lack of visibility to outside investors of intangible investments relative to tangible investments contributes to higher cost differentials between external and internal financing for the former. Such cost differentials cause internally generated CFO to be a more important determinant of the likelihood that investment opportunities are realized when investments are intangible than when tangible. The lower accrual response coefficients are consistent with the premise that deficiencies in the measurement of asset values and their expiration cause accruals to be less informative when investments are intensive in intangible assets.

The second partitioning is based on the extent of availability of liquid financial resources within the firm to exploit investment opportunities. We find that both CFO response coefficients and accrual response coefficients are higher when investment opportunities are moderately high and internal liquid resources to exploit these opportunities are scarce. This finding supports the explanation that when there is a scarcity of internal resources to exploit investment opportunities, financing cost differentials cause CFO to be an important determinant of value.

Overall, our results show that the disaggregation of earnings into CFO and accruals is useful in understanding how and why the value-relevance of earnings varies with investment opportunities. Evidence on the relatively high value-relevance of CFO and low value-relevance of accruals for high-growth companies is potentially of interest to both analysts and accounting regulators. The study demonstrates that variation in earnings value-relevance with investment opportunities is determined by the interplay of multiple factors and is therefore more complex than indicated by extant research.

REFERENCES

Ahmed, A. 1994. Accounting earnings and future economic rents: An empirical analysis. *Journal of Accounting and Economics* 17: 377–400.

Ali, A., and P. Zarowin. 1992. The role of earnings levels in annual earnings-returns studies. *Journal of Accounting Research* 30: 286–296.

———. 1994. The incremental information content of earnings, working capital from operations, and cash flows. *Journal of Accounting Research* 32: 61–74.

Amir, E., and B. Lev. 1996. Value-relevance of nonfinancial information: The wireless communications industry. *Journal of Accounting and Economics* 22: 3–30.

Anderson, C. W., and L. Garcia-Feijoo. 2006. Empirical evidence on capital investment, growth options, and security returns. *The Journal of Finance* 61: 171–194.

Anthony, J. H., and K. Ramesh. 1992. Association between accounting performance measures and stock prices: A test of the life cycle hypothesis. *Journal of Accounting and Economics* 15: 203–227.

Baber, W. R., S. N. Janakiraman, and S.-H. Kang. 1996. Investment opportunities and the structure of executive compensation. *Journal of Accounting and Economics* 21: 297–318.

Barth, M. E., W. H. Beaver, J. R. M. Hand, and W. R. Landsman. 1999. Accruals, cash flows and equity values. *Review of Accounting Studies* 4: 205–229.

Bernard, V. L. 1987. Cross-sectional dependence and problems in inference in market-based accounting research. *Journal of Accounting Research* 25: 1–48.

———, and T. L. Stober. 1989. The nature and amount of information in cash flows and accruals. *The Accounting Review* 64: 624–652.

Bodnar, G. M., and J. Weintrop. 1997. The valuation of the foreign income of U.S. multinational firms: A growth opportunities perspective. *Journal of Accounting and Economics* 24: 69–97.

Bowen, R., M. D. Burgstahler, and L. A. Daley. 1987. The incremental information content of accruals versus cash flows. *The Accounting Review* 62: 723–747.

Brown, L. D., P. A. Griffin, R. L. Hagerman, and M. E. Zmijewski. 1987. An evaluation of alternative proxies for the market's assessment of unexpected earnings. *Journal of Accounting and Economics* 9: 159–193.

Bureau of Labor Statistics 2006. *Consumer Price Index for All Urban Consumers: All Items*. Washington, D.C.: U.S. Department of Labor.

Chen, P., and G. Zhang. 2007. How do accounting variables explain stock price movements? Theory and evidence. *Journal of Accounting and Economics* 43: 219–244.

Cheng, A., C-S. Liu, and T. Schaefer. 1996. Earnings permanence and the incremental information content of cash flows from operations. *Journal of Accounting Research* 34: 173–181.

Collins, D. W., and S. P. Kothari. 1989. An analysis of inter-temporal and cross-sectional determinants of earnings response coefficients. *Journal of Accounting and Economics* 11: 143–181.

Dechow, P. 1994. Accounting earnings and cash flows as measures of firm performance: The role of accounting accruals. *Journal of Accounting and Economics* 18: 3–42.

Easton, P. D., and M. E. Zmijewski. 1989. Cross-sectional variation in the stock market response to accounting earnings announcements. *Journal of Accounting and Economics* 11: 117–141.

——, and T. S. Harris. 1991. Earnings as an explanatory variable for returns. *Journal of Accounting Research* 29: 19–36.

Fama, E. F., and K. R. French. 1992. The cross-section of expected returns. *The Journal of Finance* 47: 427–465.

Federal Reserve Board. 2004. *Flow of Funds Accounts of the United States.* March 4. Washington, D.C.: Board of Governors of the Federal Reserve System.

Financial Accounting Standards Board (FASB). 1978. *Objectives of Financial Reporting by Business Enterprises.* Statement of Financial Accounting Concepts No. 1. Stamford, CT: Financial Accounting Standards Board.

Freeman, R. N., and S. Y. Tse. 1992. A nonlinear model of security price responses to unexpected earnings. *Journal of Accounting Research* 30: 185–209.

Gaver, J. J., and K. M. Gaver. 1993. Additional evidence on the association between the investment opportunity set and corporate financing, dividend, and compensation policies. *Journal of Accounting and Economics* 16: 125–160.

Gu, F., and B. Lev. 2004. The information content of royalty income. *Accounting Horizons* 18: 1–12.

Hayn, C. 1995. The information content of losses. *Journal of Accounting and Economics* 20: 125–153.

Hubbard, R. G. 1998. Capital-market imperfections and investment. *Journal of Economic Literature* 36: 193–225.

Huber, P. 1967. The behavior of maximum likelihood estimates under nonstandard conditions. In *Proceedings of the Fifth Annual Berkeley Symposium on Mathematical Statistics and Probability,* Vol. 1, edited by L. M. LeCam, and J. Neyman, 221–233. Berkeley, CA: University of California Press.

Jensen, M. C., and W. H. Meckling. 1976. Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics* 3: 305–360.

——. 1986. Agency costs of free cash flow, corporate finance, and takeovers. *The American Economic Review* 76: 323–329.

Johnson, M., and D-W. Lee. 1994. Financing constraints and the role of cash flow from operations in the prediction of future profitability. *Journal of Accounting, Auditing & Finance* 9: 619–652.

Kaplan, S. N., and L. Zingales. 1997. Do investment-cash flow sensitivities provide useful measures of financing constraints? *The Quarterly Journal of Economics* 112: 169–215.

Kormendi, R. C., and R. Lipe. 1987. Earnings innovations, earnings persistence, and stock prices. *Journal of Business* 60: 323–345.

Lev, B., and S. R. Thiagarajan. 1993. Fundamental information analysis. *Journal of Accounting Research* 31: 190–215.

——, and P. Zarowin. 1999. The boundaries of financial reporting and how to extend them. *Journal of Accounting Research* 37: 353–385.

Lindenberg, E., and S. Ross. 1981. Tobin's q and industrial organization. *Journal of Business* 54: 1–32.

Lipe, R., L. Bryant, and S. Widener. 1998. Do nonlinearity, firm-specific coefficients, and losses represent distinct factors in the relation between stock returns and earnings? *Journal of Accounting and Economics* 25: 195–204.

Modigliani, F., and M. Miller. 1958. The cost of capital, corporation finance and the theory of investment. *The American Economic Review* 48: 261–297.

Myers, S. C., and N. S. Majluf. 1984. Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics* 13: 187–221.

Nakamura, L. 2003. A trillion dollars a year in intangible investment and the new economy. In *Intangible Assets: Values, Measures and Risks*, edited by J. Hand, and B. Lev. Oxford, U.K.: Oxford University Press.

Oliner, S. D., and G. D. Rudebusch. 1992. Sources of the financing hierarchy for business investment. *The Review of Economics and Statistics* 74: 643–654.

Opler, T., L. Pinkowitz, R. Stulz, and R. Williamson. 1999. The determinants and implications of corporate cash holdings. *Journal of Financial Economics* 52: 3–46.

Ou, J., and S. Penman. 1989. Accounting measurement, price-earnings ratio, and the information content of security prices. *Journal of Accounting Research* 27: 111–144.

Pfeiffer, R. J., P. T. Elgers, M. H. Lo, and L. L. Rees. 1998. Additional evidence on the incremental information content of cash flows and accruals: The impact of errors in measuring market expectations. *The Accounting Review* 73: 373–385.

———, and ———. 1999. Controlling for lagged stock price responses in pricing regression: An application to the pricing of cash flows and accruals. *Journal of Accounting Research* 37: 239–249.

Rayburn, J. D. 1986. The association of operating cash flow and accruals with security returns. *Journal of Accounting Research* 24: 112–133.

Sloan, R. G. 1996. Do stock prices fully reflect information in accruals and cash flows about future earnings? *The Accounting Review* 71: 289–315.

Smith, C. W., and R. L. Watts. 1992. The investment opportunity set, and corporate financing, dividend and compensation policies. *Journal of Financial Economics* 32: 263–292.

White, H. 1980. A heteroscedasticity-consistent covariance matrix estimator and a direct test for heteroscedasticity. *Econometrica* 48 (May): 817–838.

THE ACCOUNTING REVIEW
Vol. 83, No. 4
2008
pp. 1041–1081

American Accounting Association
DOI: 10.2308/accr.2008.83.4.1041

Relationship-Specific Investments and Earnings Management: Evidence on Corporate Suppliers and Customers

Kartik Raman
Bentley College

Husayn Shahrur
Bentley College

ABSTRACT: We examine the determinants and consequences of earnings management by firms in the context of their relationships with suppliers and customers. We find that industry-level proxies for relationship-specific investments by suppliers/customers are positively associated with the magnitude of discretionary accruals, volatility of earnings, and the frequency of large earnings increases. We also find that firm-level proxies for the intensity of relationship-specific investments by actual suppliers are positively related to the magnitude of discretionary accruals. In addition, earnings management by the firm in one period is positively related to the magnitude of R&D investments by suppliers and customers in the next period. However, we find that earnings management adversely affects the duration of customer-supplier relationships. Overall, our findings suggest that earnings management is used opportunistically to influence the perception of suppliers/customers about the firm's prospects.

Keywords: *earnings management; accruals; relationship-specific investments; suppliers; customers.*

Data Availability: *All data are obtained from publicly available sources.*

I. INTRODUCTION

The firm's dealings in the input and output markets often entail relationship-specific investments by its suppliers and customers.[1] Since these investments are specialized to the firm, their value to the customers and suppliers depends on the future prospects of the business relationship with the firm. Consequently, the perception of these stakeholders about the firm's

We thank two anonymous referees, Dan Dhaliwal (the Editor), Dominique Haughton, Paul Healy, Sudarshan Jayaraman, Jayant Kale, Emad Mohammad, Tom Noe, Lakshmanan Shivakumar, Ajay Subramanian, Anand Venkateswaran, and seminar participants at Bentley College and the 2006 Financial Management Association meetings for helpful comments.

Editor's note: This paper was accepted by Dan Dhaliwal.

---

[1] As noted by Williamson (1975) and others, relationship-specific assets are those that support specific transactions between the firm and its stakeholders. The assets are termed relationship-specific because the value derived from their use outside the relationship is less than that within the relationship.

Submitted: June 2006
Accepted: January 2008
Published Online: July 2008

business prospects affects their incentive to undertake such investments. If earnings management helps the firm influence nonfinancial stakeholders, as suggested by the majority of CFOs surveyed by Graham et al. (2005), then the characteristics of the relationship between a firm and its suppliers and customers should affect the earnings management decision.

Although the evidence on capital market motives for earnings management is abundant, few studies have examined the role of the firm's suppliers and customers in determining financial reporting decisions. Recognizing the importance of stakeholders to accounting decisions, Bowen et al. (1995) find that stakeholders' implicit claims affect firms' choice of income-increasing accounting methods. We contribute to this line of research by examining the (1) determinants and (2) consequences of earnings management in the context of the firm's relationships with its suppliers and customers. First, we examine whether supplier- and customer-related factors play a role in determining the magnitude of firms' earnings management. Specifically, we pose the two following questions: Do firms manage their earnings more when they operate in environments where relationship-specific investments by suppliers/customer are more likely? Does the supplier-/customer-motivated earnings management play an informational or an opportunistic role?

Second, we examine the consequences of firms' earnings management on the relationships with suppliers and customers. In particular, we address the following questions: does earnings management by the firm affect the magnitude of relationship-specific investments undertaken by suppliers/customers? How does earnings management affect the duration of firms' relationships with customers and suppliers?

A potential challenge in empirically analyzing these issues lies in assembling data on variables that represent the characteristics of each type of stakeholder. Bowen et al. (1995) note that the firm-specific variables used in their study to proxy for implicit claims by stakeholders, such as the firm's research and development (R&D) and advertising intensities, represent broad firm characteristics and are not uniquely linked to a particular type of stakeholder. Based on Fee et al. (2006) and following Kale and Shahrur (2007), we measure the importance of relationship-specific investments by suppliers and customers using the R&D intensity of the firm's supplier and customer *industries*, and that of the firm's *actual* suppliers and customers.[2] In addition, to capture business environments in which relationship-specific investments are likely to exist even in the absence of R&D investments, we use industry-level variables that capture the intensity of strategic alliances and joint ventures among firms in supplier and customer industries. We also construct firm-level variables that capture the existence of alliances between the firm and its actual suppliers and customers.

Our examination of the relation between the firm's earnings management and relationship-specific investments by its suppliers and customers is motivated by two main arguments from prior research. On one hand, earnings management can play an informational role: by removing transitory components from earnings, firms can smooth reported earnings to communicate information about future cash flows (e.g., Chaney and Lewis 1995; Sankar and Subramanyam 2001; Tucker and Zarowin 2006). The information about the firm's permanent level of future cash flows can help suppliers/customers to: (1) estimate the future revenues from their investment with more certainty, and (2) distinguish good-quality from poor-quality firms, thereby lowering the assessed risk of undertaking relationship-specific investments. On the other hand, earnings management might be driven by opportunism: firms can use accruals to inflate earnings and influence stakeholders' perceived revenues from the relationship. As a result, these stakeholders would be more willing to undertake relationship-specific investments.[3] This is because the size of future transactions is likely to be larger and the expected losses due to liquidation or financial distress are likely to be lower when dealing with a more profitable firm. Thus, both informational as well as opportunistic roles of earnings management imply greater use of accounting discretion by firms in environments where relationship-specific investments by suppliers and customers are more prevalent.

---

[2] Prior research suggests that relationship-specific investments are likely to exist in R&D intensive industries. We discuss this issue in greater detail in Section III.

Following prior research (e.g., Aboody et al. 2005), we use the absolute value of discretionary accruals to estimate the magnitude of earnings management. We estimate discretionary accruals using an augmented modified Jones (1991) model that controls for performance (Kothari et al. 2005) and growth (McNichols 2002). In our overall sample, which consists of 96,302 firm-year observations for the 1984-2003 period, we find that the coefficients on the industry-level proxies for relationship-specific investments by suppliers/customers are largely positive and significant in regressions explaining the absolute value of firms' discretionary accruals. The results are robust to different specifications of the models used to estimate discretionary accruals and to the inclusion of other determinants of the absolute value of discretionary accruals (Hribar and Nichols 2007). These findings are consistent with firms using greater accounting discretion when suppliers and customers are more likely to invest in relationship-specific assets.

Using firm-level data, we find that proxies for relationship-specific investments by actual suppliers are positively related to the magnitude of the firm's discretionary accruals. In contrast, we find that customer-specific variables are inversely related to the magnitude of the firm's earnings management. A potential reason for this finding is that, notwithstanding the benefits from communicating favorable prospects, firms may face a disincentive to report higher earnings when they are at a bargaining disadvantage *vis-à-vis* their customers (Bowen et al. 1995). Additional tests indicate that the inverse relation between earnings management by firms and proxies for relationship-specific investments by customers is weaker when the size of the firm relative to that of the customer is large. Our point estimates suggest that this relation is positive for firms that are larger than their customers. Thus, our findings suggest that the firm's incentive to use earnings management to portray a better financial image depends on its bargaining position *vis-à-vis* its customers.

Examining whether relationship-specific investments affect the extent to which firms smooth earnings, we find an inverse relation between the industry-level proxies for relationship-specific investments by suppliers/customers and the degree of income smoothing by firms. The volatility of earnings (relative to cash flow volatility) is higher and the correlation between changes in accruals and changes in operating cash flow is less negative when relationship-specific investments by firms in supplier/customer industries are high. These results are inconsistent with the proposition that firms smooth earnings when suppliers/customers are more likely to invest in relationship-specific assets.

To examine the potential role of opportunistic accounting discretion, we investigate whether environments characterized by high relationship-specific investments are associated with more frequent reporting of large earnings changes by firms. Using an approach similar to that in Burgstahler and Dichev (1997) and controlling for the frequency of large cash flow increases, we find that the frequency of large earnings increases is positively related to our industry-level proxies for relationship-specific investments. These results complement the evidence in Bowen et al. (1995) of a positive relation between the intensity of firms' implicit claims with stakeholders and the likelihood of adopting income-increasing accounting methods.

---

[3] While this study focuses on relationship-specific investments, firms can also manage earnings to influence other terms of their trade with suppliers/customer such as input/output prices and terms of trade credit. For instance, customers will be more willing to pay higher prices if the ability of the firm to honor its explicit or implicit commitments is perceived to be higher, which is likely to be the case for a more profitable firm (see, e.g., Bowen et al. 1995; Burgstahler and Dichev 1997).

Next, we turn to the consequences of earnings management on the firm's relationships with suppliers and customers. First, we examine the effect of the firm's earnings management on the supplier's and customer's R&D spending. In this analysis, we address a potential complication that can arise from both the firm as well as its stakeholders having incentives to manage earnings. For example, the supplier's (or customer's) R&D spending can be affected by factors influencing the own propensity to manage earnings. Thus, in regressions explaining R&D, we control for such factors by including the determinants of earnings management as controls in addition to those prescribed in the literature on R&D spending.

In regressions explaining the magnitude of R&D investments by actual suppliers, we find that the coefficient on the firm's lagged signed discretionary accruals is positive and significant when the firm's transactions with the supplier are large. We find a similar relation between the customer R&D and the firm's earnings management. Given that a firm could be a customer to one set of firms and a supplier to other firms, our overall results suggest that although a supplier influences the customer's investment behavior through earnings management, its own investment is influenced by the customer's earnings management. After considering rational-expectations-based explanations for our findings, we conclude that the evidence is more consistent with managers of supplier firms being fixated on the earnings reported by customer firms (and vice versa).

Finally, we examine the effect of earnings management on the duration of relationships between suppliers and customers. Using duration analysis with data on customer-supplier pairs, we find that the relationships are more likely to terminate sooner when the magnitude of discretionary accruals for either the customer or supplier is larger. The results suggest that an important consequence of earnings management is the cost attributable to the termination of the firm's relationships with suppliers and customers.

To the best of our knowledge, this is the first study to uniquely associate the characteristics of suppliers and customers with earnings management by firms. The study contributes to a growing body of literature relating relationship-specific investments by nonfinancial stakeholders to corporate decisions such as capital structure and cross-equity ownership (e.g., Fee et al. 2006; Kale and Shahrur 2007). Building on earlier work by Bowen et al. (1995), we provide evidence on the determinants and consequences of earnings management in the context of the firm's relationships with suppliers and customers.

This paper is organized as follows. Section II develops the hypotheses and discusses the related literature. Section III describes our sample and the construction of the variables used in our analysis. Section IV presents our results. Our conclusions are provided in Section V.

II. HYPOTHESES AND RELATED LITERATURE

Supplier- and Customer-Related Determinants of Earnings Management

The firm's dealings with suppliers and customers often involve relationship-specific investments. Because such specialized investments have characteristics that are specific to a particular firm, their value is lower outside the relationship (see, e.g., Williamson 1975). The value of the relationship-specific investment to the supplier/customer depends on the firm's future prospects for at least two reasons. First, to the extent the size of future transactions is correlated with the firm's prospects, the supplier/customer's expected revenues from the investment will be higher if the firm's future prospects are more favorable.

Second, the supplier/customer's investment will lose value if the firm goes out of business. In addition to the risk of liquidation, there is a high degree of uncertainty regarding the terms of future transactions because the outcomes from relationship-specific investments are not perfectly describable *ex ante* and, hence, not contractible (Tirole 1999). Thus, even if the firm is not liquidated, the supplier/customer will still be susceptible to losses if the firm behaves opportunistically by reneging on the terms of trade (Williamson 1975; Klein et al. 1978), which is more likely if the firm's future prospects worsen.[4] Because of the risks associated with relationship-specific investments, the firm will benefit from being perceived by suppliers and customers as having good prospects. Given this incentive, we consider two potential roles for earnings management: (1) informational; and (2) opportunistic.

Informational Role of Earnings Management

There is evidence suggesting that accounting accruals have incremental information about future cash flows (Bowen et al. 1987; Barth et al. 1999). In addition, theory suggests that income smoothing can be used to purge the transitory components from earnings, thereby making reported earnings informative about future profitability (e.g., Ronen and Sadan 1981; Sankar and Subramanyam 2001; Kirschenheiter and Melumad 2002; Arya et al. 2003). The empirical evidence is consistent with the notion that income smoothing improves the informativeness of earnings about future earnings and cash flows (e.g., Subramanyam 1996; Hunt et al. 2000; Tucker and Zarowin 2006). Further, Gu (2005) provides empirical evidence that income smoothing is informative about the volatility of future cash flows. Firms can also smooth income to signal superior quality (e.g., Chaney and Lewis 1995; Demski 1998).

Based on this literature, firms can use earnings management to better inform their suppliers and customers, and thus help them distinguish good-quality from poor-quality firms. A better flow of information is especially important in the presence of relationship-specific investments because it helps suppliers/customers better assess the risk of investing in specialized assets (e.g., Baiman and Rajan 2002). As a consequence, the suppliers/customers may invest more in relationship-specific assets.

Opportunistic Role of Earnings Management

In contrast to the informational role, earnings management could be used in an opportunistic manner to inflate earnings (e.g., Healy and Wahlen 1999). A number of studies provide empirical evidence on the opportunistic use of income-increasing accruals in the context of capital market events (e.g., Rangan 1998; Teoh et al. 1998), debt covenant violations (e.g., DeFond and Jiambalvo 1994; Sweeney 1994), and insider trading (e.g., Darrough and Rangan 2005). Furthermore, managers may engage in opportunistic earnings management by smoothing reported earnings (e.g., Healy 1985).[5] This view of income smoothing is echoed by practitioners and regulators, who argue that income smoothing masks information about the "true" volatility of the firm's earnings (e.g., Dechow and Skinner 2000). Moreover, Graham et al. (2005, Table 8, row 8) find no evidence that, firms smooth income to communicate information about true firm performance.

---

[4] Empirical evidence suggests that the risk of granting concessions is greater for stakeholders when dealing with financially weak firms. For example, Brown et al. (2007) find evidence consistent with suppliers granting price concessions for highly levered firms. Their results are stronger for suppliers undertaking significant relationship-specific investments. Anecdotal evidence also supports this conclusion. For instance, following a significant profit warning by General Motors, industry news reports (e.g., http://www.detnews.com/2005/autosinsider/0503/20/A01-121018.htm) indicate that the company "is chipping away at its massive operating costs by pressing suppliers for price breaks."

[5] Trueman and Titman (1988) show that firms can smooth reported earnings to influence stakeholders. However, the model assumes that investors have access only to information about the firm's earnings, but not its underlying cash flows, making the model's predictions more applicable to private rather than public firms.

In the context of our study, earnings management could be used to either inflate earnings or reduce earnings volatility, and thereby favorably influence the perception of suppliers/customers about the firm's future prospects. Consistent with this line of reasoning, the evidence in Bowen et al. (1995) suggests that firms use accounting discretion to increase reported income when stakeholders' implicit claims are high. Irrespective of whether earnings management plays an informational role or an opportunistic role, the above discussions suggest that the magnitude of earnings management by firms is likely to be higher when relationship-specific investments by suppliers/customers are more prevalent. We therefore hypothesize that:

H1: The firm's earnings management is higher if it operates in environments where relationship-specific investments by its suppliers and customers are more prevalent.

Supplier- and Customer-Related Consequences of Earnings Management

A related question is whether by managing earnings, firms are able to induce their suppliers/customers to undertake more relationship-specific investments. If suppliers and customers are able to fully undo earnings management by firms, then we should observe no empirical relation between firms' earnings management in one-period and relationship-specific investments in subsequent periods. However, if suppliers/customers are unable to detect the extent of accounting discretion by firms, then the incentive for firms to induce investments would imply that earnings management in a given period positively affects relationship-specific investments by suppliers/customers in subsequent periods.

Earnings management could also affect the incentives of the parties involved to continue the business relationship. If earnings management is opportunistic, then this may shorten the duration of the relationship because firms cannot perpetually influence suppliers/customers by reporting higher earnings as accruals from prior periods would have to be reversed over time. As evidence of myopic earnings management, Graham et al. (2005) find that a significant majority of CFOs (78 percent of those surveyed) manage earnings to meet short-term goals even if it means sacrificing long-term value. Thus, if detected, opportunism could hurt the firm's reputation and ultimately lead to the termination of the relationship.

Alternatively, if, by managing earnings, firms are able to induce suppliers/customers to undertake more relationship-specific investments, then this may result in longer relationship duration since such investments are less valuable outside the relationship. In other words, suppliers/customers will be "trapped" in the relationship due to specialized investments. Further, if earnings management is informative about future profitability, then it can help build trust between the firm and its suppliers and customers. These two arguments imply a positive association between firms' earnings management and the duration of relationships with customers/suppliers. The above discussions lead to the following hypothesis:

H2: (i) The firm's earnings management results in more relationship-specific investments by suppliers/customers.
(ii) The effect of earnings management on the duration of supplier-customer relationships is unrestricted.

III. SAMPLE AND VARIABLES

To construct our sample, we identify all firms covered by Annual Compustat for the 20-year period from 1984 to 2003. We exclude financial firms (SIC codes between 6000 and 6999) and utilities (SIC codes between 4900 and 4940). The resulting sample consists of a panel of 96,302 firm-year observations for 10,864 unique firms for which the data required to estimate our base empirical model is available. In the following sections, we describe our proxies for relationship-specific investments, earnings management, and control variables.

Variables to Proxy for Relationship-Specific Investments by Suppliers/Customers

The first set of variables we use to capture the presence of relationship-specific investments is based on the R&D intensity of the firm's suppliers and customers. Some of the R&D investments undertaken by suppliers and customers can be specific to their relationship with the firm. For example, suppliers of auto manufacturers often invest in R&D to design and develop equipments that enable them to produce highly specialized parts and accessories (Holmstrom and Roberts 1998). Software companies invest in R&D to develop software products designed for a particular business or that work within a specific operating system developed by a particular firm such as Apple Computers (Milgrom and Roberts 1992).[6] In addition to an R&D investment being itself highly specialized, R&D intensity tends to capture environments where relationship-specific investments are prevalent. The use of R&D intensity to proxy for asset specificity is abundant in the empirical literature on transactions costs. For example, Armour and Teece (1980) suggest that vertical chains that are R&D intensive are likely to have complex interstage interdependencies. Levy (1985) argues that research-intensive industries tend to involve specialized inputs that require transaction-specific investments by suppliers (see also Allen and Phillips 2000).[7] In the accounting literature, Bowen et al. (1995) use the firm's own R&D spending as a proxy for the extent to which the claims of its nonfinancial stakeholders are uniquely tied to the firm's business.

In addition to the R&D-based variables, we use the intensity of alliances and joint ventures (JVs) between the firm and its suppliers/customers as another proxy for the existence of relationship-specific investments. Theory suggests that in the presence of relationship-specific investments, firms can resort to contractual arrangements such as strategic alliances and JVs to mitigate hold up problems with suppliers and customers (e.g., Alchian and Woodward 1987). While the supplier and customer R&D measures and the alliance and JV measures are likely to be correlated, we expect the alliance and JV variables to capture relationship-specific investments even in relationships where R&D investments are not crucial.

Suppliers-/Customers-Related Variables: Industry Level

Our first approach in constructing the supplier- and customer-related variables is to rely on data for firms that operate in a given firm's supplier and customer *industries*. This approach allows us to construct proxies for supplier/customer relationship-specific investments for a large number of firms covered by Compustat. To construct these variables, we rely on the following data sources: (1) the *Use* table of the benchmark input-output (IO) accounts for the U.S. economy to identify the firm's customer and supplier industries, (2) the Compustat database to compute R&D intensities, and (3) the Securities Data Corporation (SDC) database to collect data on strategic alliances and joint ventures. The IO accounts are published by the Bureau of Economic Analysis every five years and are based primarily on data collected from economic censuses conducted by the Bureau of Census. For any pair of supplier and customer industries, the *Use* table of the IO accounts reports estimates of the dollar value of the supplier industry's output that is used as input in the production of the customer industry's output. The Appendix contains the details of how we use the IO accounts to construct the R&D variables discussed below.

---

[6] Other industries that often undertake specialized R&D investments include Aircraft Engines and Engine Parts, Biotechnology, Medical Instruments, and Semiconductors and Related Devices. This partial list is collected from reading business articles and the descriptions of supply and R&D agreements listed in the SDC database.

[7] Many R&D-intensive industries are found to have tight vertical coordination, which tend to involve highly specialized assets. These industries include Aerospace (Masten 1984), engineering (Lyons 1995), chemicals (Lieberman 1991), information technology (Ulset 1996), and electronic components (Weiss and Kurland 1997).

Industry-Level R&D Variables

To capture the R&D intensity of the firm's supplier industries, we use a weighted average of the R&D intensities of all supplier industries, where the weight captures the importance of the input bought from each supplier industry in the production of the firm's output. Formally, for each year, we measure the supplier R&D intensity for a firm in the *i*th industry as follows:

$$\textit{Supplier Industries R\&D} = \sum_{\substack{j=1 \\ i \neq j}}^{n} \textit{Supplier Industry R\&D}_j * \textit{Industry Input Coefficient}_{ji} \quad (1)$$

where n is the number of supplier industries, *Supplier Industry R&D*$_j$ is the ratio of the *j*th supplier industry's R&D to total assets, and *Industry Input Coefficient*$_{ji}$ is the dollar amount of the *j*th supplier industry's output used as input to produce one dollar of output of the *i*th industry.

Similarly, for each firm in the *i*th industry, we define the variable *Customer Industries R&D* as:

$$\textit{Customer Industries R\&D} = \sum_{\substack{j=1 \\ i \neq j}}^{n} \textit{Customer Industry R\&D}_j * \textit{Industry Percentage Sold}_{ji} \quad (2)$$

where n is the number of customer industries, *Customer Industry R&D*$_j$ is the R&D intensity of the *j*th customer industry, defined as the ratio of the industry's R&D to its total assets, and *Industry Percentage Sold*$_{ji}$ is the percentage of the *i*th industry's output that is sold to the *j*th customer industry. Since some firms sell a part of their output to noncorporate final users such as governments and individuals, we make assumptions about the R&D intensity of these users, as described in the Appendix.

The variables defined in Equations (1) and (2) are constructed at the six-digit IO industry level because the benchmark accounts are based on the IO industry classification system. This system is based on the SIC system, under which each establishment is assigned a code based on its primary activity. One of the main differences between the two systems is that the IO system redefines some secondary production of some SIC industries to other industries. Generally, the two systems are very similar, and there is a one-to-one correspondence between the majority of six-digit IO codes and four-digit SIC codes. The Appendix includes more details on the process of mapping the four-digit SIC codes to the six-digit IO codes.

Industry-Level Strategic Alliances and Joint Venture Variables

The second set of variables that proxy for relationship-specific investments is based on the intensity of strategic alliances and JVs and is measured at the industry level as follows. We first collect the alliance and JVs data from the Mergers and Acquisitions (M&A) section of the SDC database.[8] For each firm in our sample, we identify all the alliances and JVs that were announced over the sample period (1984–2003) and in which the firm is a participant. Using the input-output tables and the firm's four-digit SIC code, we identify whether at least one of the participants in the arrangement operates in a supplier or customer industry.[9] For each four-digit SIC code industry, we construct the variable, *Supplier (Customer) Alliance and JV Intensity*, as the number of alliances and JVs formed by firms in that industry and firms in a supplier (customer) industry divided by the number of firms in the industry.

---

[8] The SDC database defines a strategic alliance as "a cooperative business activity formed by two or more separate organizations for strategic purposes and which does not create an independent business entity." A joint venture is similarly defined, except that the business partners form an independent business entity.

[9] We include only supplier industries that sell more than 5 percent of their total output to the firm's industry. We also include only customer industries whose total dollar amount spent on the input bought from the firm's industry represents more than 5 percent of its total output.

Limitation of Industry-Level Variables

While the industry-level variables allow us to use a much larger sample, we recognize a potential limitation in using these variables. In particular, for a given year, the value of the industry-level variables is the same for firms in a given four-digit SIC code. In addition, because the IO accounts are constructed every five years, the weights used in the construction of the *R&D* variables are constant throughout the five-year period. Thus, the time-series variation in these variables is the result of variation in the R&D intensities of supplier/customer industries. To the extent that industry R&D intensity does not change significantly over time, most of the variation in these variables will be cross-sectional (i.e., across industries). If these variables capture industry characteristics that are correlated with accruals and not controlled for in our regressions (i.e., omitted variable problem), then our tests are less likely to capture a relation that is a manifestation of firm-level earnings management. Our use of firm-level variables and the inclusion of industry indicators in all our regressions mitigate the concern that our findings pertaining to the industry-level variables are mostly driven by omitted variables.

Key Customers-/Suppliers-Related Variables: Firm Level

The second approach we take to capture the characteristics of the firm's customers and suppliers is to rely on a subsample of firms for which we can identify key suppliers and customers. An advantage of this approach relative to the use of industry-level variables is that the analysis is based on the characteristics of the firm's actual suppliers and customers, and thus our estimates are cleaner. In addition, using firm-level variables enables us to examine the consequences of earnings management on the relationships between firms and their actual suppliers/customers.

In accordance with SFAS Nos. 14 and 131, public firms have to disclose the identity of any customer whose purchases represent more than 10 percent of the firm's total revenues. We collect this data from Compustat's Segment Tapes for 1984-2002 (see the Appendix). We then construct the R&D intensity of the firm's key customers as follows:

$$\text{Key Customers R\&D} = \sum_{j=1}^{n} \text{Key Customer R\&D}_j * \text{Customer Percentage Sold}_j \tag{3}$$

where n is the number of customers, *Key Customer R&D*$_j$ is equal to the R&D expense (scaled by assets) of the jth customer, and *Customer Percentage Sold*$_j$ is the percentage of the firm's sales to the jth customer. The resulting sample is a panel of 13,295 firm-year observations for which data necessary to compute *Key Customers R&D* and other variables are available. In addition to *Key Customers R&D*, we construct the variable *Main Customer R&D* as the R&D expense (normalized by total assets) of the customer that contributes the most to the firm's sales.

We compute the R&D intensity of the firm's suppliers as follows:

$$Key\ Suppliers\ R\&D = \sum_{j=1}^{n} \text{Key Supplier } R\&D_j * Customer\ Input\ Coefficient_j \tag{4}$$

where n is the number of suppliers, *Key Supplier* $R\&D_j$ is equal to the R&D expense (scaled by assets) of the jth supplier, and *Customer Input* $Coefficient_j$ is the ratio of the purchase from the jth supplier to the firm's total sales. This results in a panel of 5,842 firm-year observations for which we have data to estimate our base regressions. We also construct *Main Supplier R&D* as the R&D expense (normalized by total assets) of the supplier from which the customer buys most of its input (as a percentage of the customer total sales).[10]

Further, we construct a dummy variable, *Customer (Supplier) Alliance and JV Dummy*, that equals 1 if the firm announced (as reported by SDC) at least one strategic alliance or JV with one of its key customers (key suppliers) in the years preceding the observation year, and 0 otherwise.

Measures of Earnings Management

Kothari et al. (2005) suggest that when earnings management is motivated by an identifiable event (such as a seasoned equity offering), the correlation between accruals and firm performance prior to the event is likely to be high. Since our study is not based on an event type of setting, we follow Kothari et al.'s (2005) proposed alternative to the matched-firm approach by including performance (return on assets) as an independent variable in the modified Jones (1991) model regression of Dechow et al. (1995). In addition, we control for growth options (book-to-market ratio) in the modified Jones model regression because prior research suggests that firms with higher growth opportunities tend to have higher accruals (e.g., McNichols 2002; Cohen et al. 2005). We define discretionary accruals (DA) as:

$$DA_t = TA_t - NDA_t \tag{5}$$

where TA is total accruals, and NDA is nondiscretionary accruals. Following previous studies (e.g., Dechow et al. 1995), TA is defined as follows:

$$TA_t = (\Delta CA_t - \Delta CL_t - \Delta\ Cash_t + \Delta STD_t - Dep_t)/(A_{t-1}) \tag{6}$$

where ΔCA is the change in current assets (data 4), ΔCL is the change in current liabilities (data 5), $\Delta Cash$ represents the change in cash and cash equivalents (data 1), ΔSTD is the change in debt included in current liabilities (data 34), and DEP represents depreciation (data 14).

To estimate nondiscretionary accruals, we use ordinary least squares regression (with no intercept) to first estimate the parameters of the following model:

$$TA_t = \alpha_1(1/A_{t-1}) + \alpha_2(\Delta REV_t/A_{t-1} - \Delta REC_t/A_{t-1}) + \alpha_3(PPE_t/A_{t-1}) + \alpha_4(ROA_t) + \alpha_5(BM_t) + \varepsilon_t \tag{7}$$

where A represents total assets (data 6), ΔREV is the change in revenues (data12), ΔREC is the change in net receivables (data 2 minus data 67), PPE represents the amount of property, plant, and equipment (data 7), ROA is defined as the net income before extraordinary items (data 18) scaled by lagged total assets, and BM is the ratio of total assets to total assets minus book value of equity (data 60) plus market value of equity (the product of data 25 and data 199). We estimate the model in Equation (7) for each two-digit SIC code for each fiscal year in our sample. If an industry has less than 10 observations for any given year, then we estimate the model at the one-digit SIC code level. To reduce the effect of outliers on the estimates, we winsorize all variables in Equation (7) at the 1st and 99th percentiles. Discretionary accruals are then estimated as $\hat{DA}_t = TA_t - N\hat{D}A_t$, where:

---

[10] Since firms are required to disclose the identities of their important customers but not their suppliers, the firm's suppliers are determined by inverting the data set and identifying all the suppliers that report the firm as a key customer. Thus, for each customer firm, the main supplier is identified from this set of suppliers and not from a comprehensive list of suppliers. Given this limitation, the identified main supplier may not be the most important supplier to the customer firm.

$$N\hat{D}A_t = \hat{\alpha}_1(1/A_{t-1}) + \hat{\alpha}_2(\Delta REV_t/A_{t-1} - \Delta REC_t/A_{t-1}) + \hat{\alpha}_3(PPE_t/A_{t-1}) + \hat{\alpha}_4(ROA_t) + \hat{\alpha}_5(BM_t). \quad (8)$$

Discretionary accruals include both positive and negative observations. For tests designed to examine whether earnings management increases in the level of relationship-specific investments, we define the variable *Earnings Management* as the absolute value of discretionary accruals (see, e.g., Chung and Kallapur 2003; Aboody et al. 2005; Bowen et al. 2005; Hribar and Nichols 2007).[11] Examining the absolute value of discretionary accruals allows us to first establish whether relationship-specific investments are associated with greater accounting discretion. Since the informational and opportunistic incentives for earnings management can have different predictions regarding the signed discretionary accruals, one drawback of using the absolute value of discretionary accruals is that it restricts us from examining such directional predictions. To get further insights on the various motives, we conduct additional tests in Section IV that are based on the volatility of earnings (relative to cash flow volatility) and the frequency of large earnings increases. In subsequent tests, we use signed discretionary accruals to examine whether the firm's earnings management affects relationship-specific investments by its suppliers/customers.

Control Variables

In addition to variables representing relationship-specific investments, we construct firm-specific control variables that Bowen et al. (1995) use to proxy for the extent of implicit claims between a firm and its stakeholders. Thus, we use the firm's own R&D and advertising intensities, leverage, and human capital intensity. Following Hribar and Nichols (2007), we include firm characteristics that have been identified by prior research to be correlated with the absolute value of discretionary accruals (see also Bergstresser and Philippon 2006; Bowen et al. 2005). For instance, Skinner and Sloan (2002) find that growth firms experience an asymmetrically large negative price response to negative earnings surprises. Thus, the incentive to manage earnings is likely to be higher for growth firms. In addition, Hribar and Nichols (2007) suggest that the magnitude of discretionary accruals is likely to be correlated with measures of underlying operating volatility. Hence, as additional controls, we include the firm's volatility of cash flows, net income, and sales. The regressions also include year and industry indicator variables to further control for any omitted year or industry effects. To conserve space, we provide the construction of the control variables in the legend of Table 1.[12] We winsorize the dependent and independent variables at the 1st and 99th percentiles.

Table 1 provides summary statistics for our variables for the three samples: the overall sample, the subsample for which key suppliers' data is available, and the subsample with key

---

[11] Hribar and Nichols (2007) review the literature that uses the absolute value of discretionary accruals, and discuss the importance of controlling for firm characteristics when studying the propensity of earnings management.

[12] We follow Subramanyam (1996) and compute cash flow from operations for firms that had not adopted the cash flow format for years prior to 1987 as follows: OCF = Funds (item 100) − change in current assets (item 4) + change in current liabilities (item 5) + change in cash (item 1) − change in the current portion of long-term debt (item 34). We also repeat our analysis and find qualitatively similar results using the sample period 1987 to 2003.

TABLE 1
Descriptive Statistics

	Overall Sample		Subsample with Key Suppliers Data		Subsample with Key Customers Data	
Number of firm-year observations	96,302		5,842		13,295	
	Mean	**Median**	**Mean**	**Median**	**Mean**	**Median**
Earnings Management	0.084	0.052	0.058	0.038	0.0934	0.0606
Suppliers						
Supplier Industries R&D	0.008	0.006	0.009	0.005	0.011	0.009
Supplier Alliance and JV Intensity	0.136	0.010	0.348	0.061	0.141	0.050
Key Suppliers R&D	—	—	0.002	0.000	—	—
Main Supplier R&D			0.069	0.009		
Supplier Alliance and JV Dummy	—	—	0.219	0.000	—	—
Customers						
Customer Industries R&D	0.014	0.008	0.015	0.009	0.020	0.013
Customer Alliance and JV Intensity	0.111	0.000	0.169	0.000	0.186	0.020
Key Customers R&D	—	—	—	—	0.011	0.002
Main Customers R&D					0.037	0.016
Customer Alliance and JV Dummy	—	—	—	—	0.124	0.000
Firm-Specific Control Variables						
Firm R&D Intensity	0.052	0.000	0.042	0.010	0.073	0.016
Firm Advertising Intensity	0.014	0.000	0.019	0.000	0.012	0.000
Human-Capital Intensity	0.437	0.536	0.400	0.468	0.463	0.586
Firm Leverage	0.259	0.209	0.247	0.228	0.236	0.181
Firm Size	4.509	4.394	7.464	7.657	4.356	4.210
Firm Age	14.336	10.000	23.823	23.000	12.770	9.000
Book-to-Market	0.716	0.704	0.651	0.656	0.713	0.697
Return on Assets	−0.010	0.045	0.075	0.076	0.006	0.055
Free Cash Flow Dummy	0.160	0.000	0.056	0.000	0.144	0.000
Cash-Flow-to-Assets	0.001	0.059	0.084	0.095	0.003	0.055
Sales Growth	1.244	1.090	1.183	1.089	1.259	1.101
Volatility of Cash Flow	0.181	0.089	0.077	0.058	0.174	0.103
Volatility of Net Income	0.291	0.092	0.089	0.043	0.267	0.109
Volatility of Sales	0.399	0.293	0.294	0.229	0.390	0.305

This table reports descriptive statistics for the dependent and independent variables. *Earnings Management* is the absolute value of discretionary accruals. *Supplier Industries R&D (Customer Industries R&D)* is the weighted average of the R&D intensities of all supplier (customer) industries. *Supplier (Customer) Alliance and JV Intensity* is the number of strategic alliances and joint ventures established between industry firms and firms in supplier (customer) industries, divided by the number of firms in the industry. *Key Suppliers R&D (Key Customers R&D)* is the weighted average of the R&D intensities of key suppliers (key customers). *Main Supplier (Customer) R&D* is the ratio of R&D to total assets of the main

(continued on next page)

(continued on next page)

TABLE 1 (continued)

supplier (customer). *Alliance and JV Dummy* is a dummy variable that equals 1 if the firm has at least one alliance or JV established with one of its key suppliers (key customers), and 0 otherwise. *Firm R&D Intensity* is the ratio of R&D expense (data 46) to total assets (data 6). Missing values for R&D are set equal to zero. *Firm Advertising Intensity* is the ratio of advertising expense (data 45) to total assets. *Human-Capital Intensity* is 1 minus the ratio of gross property, plant, and equipment (data 7) to total assets. *Firm Leverage* is the ratio of the sum of long-term debt (data 9) and debt in current liabilities (data 34) to total assets. *Firm Size* is the natural log of the firm's total assets. *Firm Age* is the number of years in which the firm is listed on Compustat. *Book-to-Market* is the ratio of total assets to total assets minus book value of equity (data 60) plus market value of equity (product of data 25 and data 199). *Return on Assets* is the sum of net income before extraordinary items (data 18) and R&D expense (data 46) divided by total assets. *Free Cash Flow Dummy* is a dummy variable that equals 1 if the firm's free cash flow scaled by lagged current assets is less than −0.5, and 0 otherwise, and where free cash flow is the difference between operating cash flows in year $t-1$ and the average capital expenditures for the firm during the past three years. *Cash-Flow-to-Assets* is the ratio of operating cash flow (data 308) to total assets. *Sales Growth* is the ratio of current sales to lagged sales (data 12). *Volatility of Cash Flow, Net Income,* and *Sales* is the standard deviation of operating cash flows, net income, and sales, respectively. At least five observations are required to estimate the volatility measures. All variables are winsorized at the 1st and 99th percentiles. The industry indicator variables are based on the firm's two-digit historical SIC code (data 324). Since this data item is only available from 1987 onward, we use the 1987 code for years prior to 1987. If this variable is missing, we use the current SIC code.

customers' data. For the overall sample, the mean and median values of the absolute value of discretionary accruals are 0.084 and 0.052, respectively. These values are comparable to those reported in the literature (e.g., Aboody et al. 2005).[13]

The summary statistics reported in Table 1 reveal that the subsample of firms with key suppliers' data is biased toward larger firms. In this subsample, the mean *Firm Size*, computed as the natural logarithm of total assets, is 7.46 (corresponding to total assets of $1,737 million), compared to 4.51 ($90.9 million) for the overall sample, and 4.36 ($78.3 million) for the subsample with key customers' data. This pattern in the sizes of suppliers and customers is similar to that reported in other studies (e.g., Fee et al. 2006). The bias toward large customers is most likely due to the disclosure rule that firms are required to report only customers that contribute at least 10 percent to their revenues.

IV. RESULTS

Determinants of Earnings Management Using Industry-Level Variables

We test H1 by conducting ordinary least squares (OLS) regression analysis of *Earnings Management*, the absolute value of discretionary accruals, on industry-level supplier and customer variables. The basic form of our regressions is as follows:

$$\begin{aligned}\textit{Earnings Management} = \alpha \\ &+ \beta_1(\textit{Supplier Industries R\&D} \text{ or } \textit{Supplier Alliance and JV Intensity}) \\ &+ \beta_2(\textit{Customer Industries R\&D} \text{ or } \textit{Customer Alliance and JV Intensity}) \\ &+ \gamma(\textit{Control Variables}) + \varepsilon.\end{aligned}$$

---

[13] For the overall sample of 96,302 firm-year observations, and the subsamples comprising of observations available for the firm's key suppliers (5,842 firm-year observations), and those available for the key customers (13,295 firm-year observations), the correlation between the industry representations (the percentage of the sample in each two-digit SIC industry) for each pair of subsamples is at least 0.8, suggesting a high degree of homogeneity in terms of industry composition across the different samples. These results are not tabulated for the sake of brevity.

We report t-statistics based on heteroscedasticity-robust standard errors that are adjusted for clustering at the firm level.[14] The results are presented in Table 2. Consistent with the implications of H1, that firms outsourcing from R&D intensive supplier industries have higher levels of earnings management, the coefficient on *Supplier Industries R&D* in Model 1 is positive and highly significant. In addition, the coefficient on *Supplier Alliance and JV Intensity* (in Model 2) is also positive and significant, a result that further supports our hypothesis. The results for customer-specific variables also support H1. While the coefficient on *Customer Industries R&D* is insignificant in Model 1, the coefficient on *Customer Alliance and JV Intensity* is positive and statistically significant in Model 2.

Firms can decrease suppliers/customers' assessed risk of relationship-specific investments by reducing leverage to lower the likelihood of financial distress or liquidation (e.g., Titman 1984; Kale and Shahrur 2007). However, financially troubled firms may be unable to reduce leverage if they are constrained from raising equity capital under reasonable terms. Consequently, if firms manage earnings to enhance the perception of suppliers/customers, then this incentive should be more important for firms in financial difficulty.

In Models 3 and 4, we present the coefficients on the interactions between the proxies for relationship-specific investments and the firm's financial health. The proxy for the firm's financial health is *Zscore Dummy*, a binary variable that equals 1 if the firm-year observation for Altman's Z is in the bottom quartile among all firm-years, and 0 otherwise.[15] Note that Altman's Z is lower for firms in poor financial health. If enhancing the financial image with suppliers/customers is more important for financially weaker firms, as suggested by the evidence in Graham et al. (2005), then we expect a positive coefficient on the interaction terms. The evidence in Models 3 and 4 indicates positive and significant coefficients on three of the four interaction terms, *Supplier Industries R&D**Zscore Dummy, Customer Industries R&D**Zscore Dummy, and Customer Alliance and JV Intensity**Zscore Dummy.*[16]

We find that the coefficients on the supplier and customer variables are economically significant. We use the estimated coefficients from Models 1 and 2 of Table 2 to compute the change in *Earnings Management* if a firm moves from the 5th percentile value to the 95th percentile value of a specific independent variable, holding all the other independent variables at their sample means. For the variables *Supplier Industries R&D*, *Supplier SA and JV Intensity*, and *Customer SA and JV Intensity*, we find that, moving from the 5th to 95th percentile changes *Earnings Management* by about 0.9, 0.6, and 0.5 percent of total assets, respectively. Compared to the median value

---

[14] We also conduct between-firm regressions, where the time-series average of the dependent variable is regressed against the time-series averages of the independent variables. The results (not reported in a table) are similar to those obtained using OLS regressions.

[15] Altman's Z is computed as 3.3*data178 / data6 + 1.2*(data4 – data5) / data6 + data12 / data6 + 0.6*data199*data25 / (data9 + data34) + 1.4*data36 / data6. We give the value at the 99th percentile of Altman's Z for firms with zero debt (data9 + data34 = 0). Excluding these observations yields similar results. Further, defining *Zscore Dummy* based on the median Altman's Z yields qualitatively similar results, albeit with weaker statistical significance.

[16] Other mechanisms used to mitigate the incentive problems with suppliers/customers include (but not limited to): (1) Vertical integration; (2) the presence of long-term contracts, which limits repeated *ex post* negotiations (Williamson 1979, 1983; Klein et al. 1978; Joskow 1987); and (3) cross-equity ownership (e.g., Fee et al. 2006). Due to data limitation, we only conduct analysis on the effect of vertical integration on our findings. Thus, we examine whether the positive relations between *Earnings Management* and the proxies for relationship-specific investments are weaker for vertically integrated firms. Since such firms have fewer incentives to influence suppliers and customers, these firms are expected to exhibit a lower propensity for earnings management. Using Compustat, we construct dummy variables that capture whether a firm in our sample has a segment in a supplier/customer industry. We then interact these variables with the respective proxy for relationship-specific investments and include them in a model that also contains the Z-score-based interactions. In unreported results, we find that the coefficients on the four vertical integration-based interactions terms are negative, with three of them statistically significant. The results on the other variables are qualitatively similar to those reported below.

TABLE 2

Regression Analysis of Absolute Value of Discretionary Accruals Industry-Level Supplier and Customer Variables

	Model 1	Model 2	Model 3	Model 4
Intercept	0.081***	0.084***	0.092***	0.092***
	(8.44)	(8.80)	(8.71)	(8.69)
Supplier Variables				
Supplier Industries R&D	0.398***		0.324***	
	(4.84)		(3.86)	
*Supplier Industries R&D * Zscore Dummy*			0.398**	
			(2.14)	
Supplier Alliance and JV Intensity		0.008***		0.009***
		(6.67)		(6.91)
*Supplier Alliance and JV Intensity * Zscore Dummy*				−0.002
				(−1.00)
Customer Variables				
Customer Industries R&D	0.000		−0.015	
	(0.01)		(−0.43)	
*Customer Industries R&D * Zscore Dummy*			0.091*	
			(1.89)	
Customer Alliance and JV Intensity		0.006***		0.004***
		(3.61)		(2.61)
*Customer Alliance and JV Intensity * Zscore Dummy*				0.008*
				(1.77)
Control Variables				
Zscore Dummy			0.003**	0.007***
			(2.32)	(5.83)
Firm R&D Intensity	0.010	0.012**	0.009	0.011*
	(1.57)	(1.97)	(1.38)	(1.84)
Firm Advertising Intensity	0.028**	0.028**	0.029**	0.029**
	(2.47)	(2.45)	(2.55)	(2.52)
Human-Capital Intensity	0.014***	0.014***	0.015***	0.015***
	(10.91)	(11.27)	(11.29)	(11.51)
Leverage	0.017***	0.017***	0.011***	0.012***
	(9.47)	(9.39)	(5.43)	(5.55)
Firm Size	−0.007***	−0.008***	−0.007***	−0.007***
	(−33.13)	(−33.69)	(−32.55)	(−33.37)
Firm Age	−0.003***	−0.003***	−0.003***	−0.003***
	(−10.28)	(−10.28)	(−10.35)	(−10.23)
Book-to-Market	−0.028***	−0.029***	−0.030***	−0.030***
	(−26.27)	(−26.47)	(−27.05)	(−27.30)

(continued on next page)

TABLE 2 (continued)

	Model 1	Model 2	Model 3	Model 4
Return on Assets	−0.044***	−0.044***	−0.043***	−0.043***
	(−18.55)	(−18.61)	(−18.08)	(−18.15)
Free Cash Flow Dummy	0.000	0.000	−0.001	−0.001
	(0.09)	(0.00)	(−0.69)	(−0.84)
Operating Cash Flow	0.007**	0.007**	0.007**	0.007**
	(2.17)	(2.31)	(2.33)	(2.38)
Sales Growth	0.010***	0.010***	0.010***	0.010***
	(16.40)	(16.41)	(16.38)	(16.36)
Volatility of Cash Flows	0.016***	0.016***	0.016***	0.016***
	(5.81)	(5.80)	(5.73)	(5.69)
Volatility of Net Income	−0.004***	−0.004***	−0.004***	−0.004***
	(−3.75)	(−3.75)	(−3.72)	(−3.70)
Volatility of Sales	0.022***	0.022***	0.022***	0.022***
	(13.56)	(13.32)	(13.53)	(13.30)
Industry and Year Indicators	Yes	Yes	Yes	Yes
Number of Observations	96,302	96,302	95,717	95,717
Adjusted R^2	17.99%	18.04%	18.06%	18.09%

---

*, **, *** Indicate statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively.

The dependent variable is *Earnings Management*, which is the absolute value of discretionary accruals. *Supplier (Customer) Industries R&D* is the weighted average of the R&D intensities of all supplier (customer) industries. *Supplier (Customer) Alliance and JV Intensity* is the number of strategic alliances and joint ventures established between industry firms and firms in supplier (customer) industries, divided by the number of firms in the industry. *Zscore Dummy* is a dummy variable that equals 1 if the firm is in the bottom quartile of Altman Z, and 0 otherwise. The control variables are described in Table 1. The coefficient on *Firm Age* is multiplied by 10. The reported t-values are based on heteroscedasticity robust standard errors adjusted for clustering at the firm level.

of *Earnings Management*, these changes are significant and represent 16.79, 10.36, and 9.41 percent changes, respectively, in the absolute value of discretionary accruals.

The coefficients on *Firm Advertising Intensity*, *Human-Capital Intensity*, and *Leverage* are all positive and highly significant. These results extend the findings in Bowen et al. (1995) by suggesting that implicit contracting with stakeholders affects the firm's earnings management decision. The results for other control variables are largely consistent with the literature.

Analysis of Earnings Management Using Key Supplier and Customer Variables

In Tables 3 and 4, we relate *Earnings Management* to the R&D intensities of key suppliers and customers, and to the existence of strategic alliances between firms and their key suppliers or customers. Table 3 (4) presents results for key supplier (customer) variables for one model that uses the alliance dummy, three OLS specifications based on the lagged values of the R&D

TABLE 3

Regression Analysis of Absolute Value of Discretionary Accruals Firm-Level Key Supplier Variables

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5 (2SLS)**
Intercept	0.170***	0.075***	0.077***	0.076***	−0.047
	(14.14)	(2.75)	(2.74)	(2.69)	(−0.59)
Supplier Variables					
Supplier Alliance and JV Dummy	0.008***				
	(3.02)				
Lagged Key Suppliers R&D		0.801***			
		(3.08)			
Lagged Main Supplier R&D			0.023**	0.020**	
			(2.29)	(2.08)	
*Lagged Main Supplier R&D * Supplier Importance*				0.061	
				(1.55)	
Main Supplier R&D					0.031*
					(1.82)
Supplier Importance				0.013	
				(0.72)	
Control Variables					
Firm R&D Intensity	0.062*	0.69**	0.067*	0.067*	0.099**
	(1.84)	(2.02)	(1.93)	(1.87)	(2.30)
Firm Advertising Intensity	0.011	0.012	0.015	0.016	0.004
	(0.42)	(0.45)	(0.58)	(0.64)	(0.14)
Human-Capital Intensity	0.015***	0.014***	0.015***	0.015***	0.016***
	(4.16)	(4.03)	(4.20)	(4.18)	(3.78)
Leverage	0.002	0.003	0.003	0.004	0.008
	(0.25)	(0.43)	(0.45)	(0.46)	(0.87)
Firm Size	−0.004***	−0.003***	−0.003***	−0.003***	−0.003***
	(−5.44)	(−4.58)	(−4.55)	(−4.30)	(−3.60)
Firm Age	−0.003***	−0.003***	−0.003***	−0.003***	0.000***
	(−4.95)	(−4.50)	(−4.47)	(−4.50)	(−4.25)
Book-to-Market	−0.010*	−0.007	−0.006	−0.006	0.000
	(−1.95)	(−1.38)	(−1.34)	(−1.34)	(−0.08)
Return on Assets	−0.054***	−0.053***	−0.050***	−0.050**	−0.036*
	(−3.19)	(−2.75)	(−2.59)	(−2.53)	(−1.65)
Free Cash Flow Dummy	0.060	0.007	0.007	0.007	0.011*
	(1.12)	(1.47)	(1.46)	(1.42)	(1.81)
Operating Cash Flow	0.072***	0.086***	0.086***	0.086***	0.107***
	(3.40)	(4.35)	(4.37)	(4.45)	(4.46)
Sales Growth	0.018***	0.020***	0.020***	0.020***	0.019***

(continued on next page)

TABLE 3 (continued)

	Model 1	Model 2	Model 3	Model 4	Model 5 (2SLS)
	(4.38)	(4.60)	(4.50)	(4.47)	(3.81)
Volatility of Cash Flows	0.060**	0.075***	0.075***	0.075***	0.069*
	(2.17)	(2.65)	(2.65)	(2.63)	(1.82)
Volatility of Net Income	0.009	0.023	0.024	0.024	0.040
	(0.56)	(1.25)	(1.39)	(1.36)	(1.60)
Volatility of Sales	0.027***	0.025***	0.024***	0.024***	0.025***
	(4.40)	(4.14)	(4.06)	(4.08)	(3.68)
Industry Indicators	Yes	Yes	Yes	Yes	Yes
Year Indicators	Yes	Yes	Yes	Yes	Yes
Number of Observations	5,842	5,533	5,533	5,533	4,173
Adjusted R^2	19.85%	19.53%	19.97%	19.96%	18.62%

---

*, **, *** Indicate statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively.

The dependent variable is *Earnings Management*, which is the absolute value of discretionary accruals. Models 1–4 report results of OLS regressions, while Model 5 reports results of the second stage of a two-stage least squares (2SLS) model, where *Earnings Management* and *Main Supplier R&D* are treated as endogenous variables. *Supplier Alliance and JV Dummy* is a dummy variable that equals 1 if the firm has at least one alliance or JV established with one of its key suppliers, and 0 otherwise. *Lagged Key Suppliers R&D* is lagged value of the weighted average of the R&D intensities of key suppliers. *(Lagged) Main Supplier R&D* is the (lagged) value of the R&D of the main supplier, normalized by total assets. *Supplier Importance* is the dollar purchases from the main supplier divided by the firm's total sales. The control variables are described in Table 1. The coefficient on *Firm Age* is multiplied by 10. For the 2SLS regression in Model 5, we estimate the predicted values of *Main Supplier R&D* using the following instruments in the first stage. Size is the log of total assets (item 6). *Book-to-Market* is total assets (item 6) divided by the sum of the book value of debt and market value of common equity (item 6 – item 60 + item 199*item 25). *Sales Growth* is the one-year growth in total sales (item 12). *Stock Return* is the return on common stock in the prior year (collected from CRSP). *Leverage* is the equal to the sum of the book values of long-term debt and debt in current liabilities (items 9 and 34) divided by the book value of assets. *Operating Cash Flow Surplus* is cash from assets-in-place (item 308 – item 125 + item 46) divided by total assets (item 6). *Financing Cash Flow* is cash flow from financing activities (CFFA) (item 313) scaled by total assets. If item 313 is missing, then we compute CFFA as Sale of Common and Preferred Stock (data108) – Purchase of Common and Preferred Stock (data115) – Cash Dividends (data127) + Issuance of Long-Term Debt (data111) – Reduction in Long-Term Debt (data114) + Changes in Current Debt (data301). Cash is cash and short-term investments (item 1) divided by total assets (item 6). *Capital Expenditures* is capital expenditures (item 128) divided by total assets (item 6). *SGA Expenses* is selling, general, and administrative expenses (item 189) divided by total assets (item 6). *Industry R&D* is the sum of R&D (item 46) for firms in the four-digit SIC industry divided by the sum of total assets (item 6) for the same firms. The reported t-values are based on heteroscedasticity robust standard errors adjusted for clustering at the firm level.

TABLE 4

Regression Analysis of Absolute Value of Discretionary Accruals Firm-Level Key Customer Variables

	Model 1	Model 2	Model 3	Model 4	Model 5 2SLS
Intercept	0.040***	0.163***	0.173***	0.168***	0.206***
	(4.14)	(5.54)	(5.53)	(5.02)	(5.93)
Customer Variables					
Customer Alliance and JV Dummy	–0.012***				
	–(4.08)				
Lagged Key Customers R&D		−0.111**			
		(−1.99)			
Lagged Main Customer R&D			−0.057**	−0.013	
			(−2.40)	(−0.39)	
*Lagged Main Customer R&D * Customer Importance*				−0.184*	
				(−1.73)	
Main Customer R&D					−0.094***
					(−3.13)
Customer Importance				0.016*	
				(1.86)	
Control Variables					
Firm R&D Intensity	0.024*	0.021**	0.021	0.021	0.023
	(1.72)	(2.25)	(1.43)	(1.46)	(1.51)
Firm Advertising Intensity	0.094***	0.096***	0.095***	0.099***	0.105***
	(2.83)	(3.78)	(2.80)	(2.89)	(2.87)
Human-Capital Intensity	0.020***	0.019***	0.020***	0.020***	0.022***
	(6.44)	(6.90)	(6.27)	(6.21)	(6.20)
Leverage	0.018***	0.016***	0.016***	0.016***	0.016***
	(3.66)	(4.49)	(3.16)	(3.17)	(2.95)
Firm Size	−0.007***	−0.008***	−0.008***	−0.007***	−0.008***
	(−11.86)	(−14.84)	(−12.18)	(−11.59)	(−11.09)
Firm Age	−0.005***	−0.004***	−0.004***	−0.004***	−0.005***
	(−5.52)	(−5.60)	(−4.77)	(−4.68)	(−4.99)
Book-to-Market	−0.032***	−0.031***	−0.032***	−0.032***	−0.033***
	(−11.29)	(−12.44)	(−11.01)	(−10.92)	(−10.49)
Return on Assets	−0.046***	−0.048***	−0.046***	−0.046***	−0.042***
	(−7.53)	(−14.02)	(−6.86)	(−6.85)	(−5.81)
Free Cash Flow Dummy	0.005*	0.005*	0.006*	0.005*	0.007*
	(1.68)	(1.89)	(1.73)	(1.68)	(1.88)
Operating Cash Flow	0.016**	0.013**	0.013	0.013	0.011
	(2.03)	(2.48)	(1.57)	(1.55)	(1.19)

(continued on next page)

TABLE 4 (continued)

	Model 1	Model 2	Model 3	Model 4	Model 5 2SLS
Sales Growth	0.014***	0.016***	0.016***	0.016***	0.016***
	(8.61)	(14.17)	(9.02)	(8.97)	(8.17)
Volatility of Cash Flows	−0.002	−0.001	−0.001	−0.001	−0.003
	(−0.35)	(−0.16)	(−0.12)	(−0.10)	(−0.35)
Volatility of Net Income	−0.002	−0.003	−0.003	−0.003	−0.003
	(−0.50)	(−1.52)	(−0.96)	(−0.95)	(−0.76)
Volatility of Sales	0.032***	0.030***	0.031***	0.031***	0.032***
	(6.61)	(9.65)	(6.17)	(6.14)	(6.23)
Industry and Year Indicators	Yes	Yes	Yes	Yes	Yes
Number of Observations	13,295	13,100	13,100	13,100	11,356
Adjusted R^2	17.00%	16.25%	15.96%	15.99%	15.92%

*, **, *** Indicate statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively.

The dependent variable is *Earnings Management*, which is the absolute value of discretionary accruals. Models 1–4 report results of OLS regressions, while Model 5 reports results of the second stage of a two-stage least squares (2SLS) model, where *Earnings Management* and *Main Customer R&D* are treated as endogenous variables. *Customer Alliance and JV Dummy* is a dummy variable that equals 1 if the firm has at least one alliance or JV established with one of its key customers, and 0 otherwise. *Lagged Key Customers R&D* is lagged value of the weighted average of the R&D intensities of key Customers. (*Lagged*) *Main Customer R&D* is the (lagged) value of the R&D of the main customer, normalized by total assets. *Customer Importance* is the percentage of the firm's sales made to the main customer. The coefficient on *Firm Age* is multiplied by 10. The control variables are described in Table 1. The variables used in the first stage of the 2SLS model (Model 5) are described in Table 3. The reported t-values are based on heteroscedasticity robust standard errors adjusted for clustering at the firm level.

measures, and one model based on a two-stage least squares (2SLS) estimation.[17] We use these specifications to alleviate endogeneity concerns arising from the potentially simultaneous relation between earnings management and R&D investments. For instance, as discussed in Section II, it is possible that the firm's earnings management affect the R&D investments by suppliers and customers.[18]

The results reported in Table 3 indicate that the coefficients on the supplier-related proxies for relationship-specific investments are positive and significant in all presented models. In Model 1, the coefficient on *Supplier Alliance and JV Dummy* is equal to 0.008, which is statistically significant at the 1 percent level. In Models 2 and 3, the independent variables of interest are the lagged value of *Key Suppliers R&D* and *Main Supplier R&D*, respectively. The coefficients on both these variables are positive and significant.[19] The coefficients on the supplier-related variables in Models 1–3 are also economically significant. For instance, relative to the median value of *Earnings Management*, a change in the value of *Key Suppliers R&D* and *Main Supplier R&D* from the 5th to 95th percentile results in a 12.3 percent and 13.7 percent change in the absolute value of discretionary accruals, respectively.

---

[17] Recall that in the analysis reported in Table 2, we include both the supplier as well as the customer variables in the same regressions. We do not use the same specification in this section since the number of firms for which we can measure the R&D intensity of both suppliers and customers is very small (only 895 firm-year observations). Using this subsample yields positive but largely insignificant coefficients on the supplier and customer R&D variables, while the results related to the alliance variables are qualitatively similar to those reported below. Further, to mitigate concerns arising from omitted variables, in the regressions analyzing supplier (customer) effects, we include *Customer Industries R&D* (Supplier Industries *R&D*) as an additional control variable. The untabulated results from this specification are similar to those reported in the study.

[18] We do not conduct 2SLS models for the tests based on industry-level supplier and customer data (Table 2) since endogeneity issues are less relevant in regressions that use industry-level variables. This is because it is unlikely that variables measured at the industry level are determined by the earnings management of a particular firm.

Using an interaction term in Model 4, we examine whether the positive coefficient on (lagged) *Main Supplier R&D* is stronger when the main supplier is more important to the firm. We determine the importance of the main supplier to the firm based on *Supplier Importance*, the ratio of the firm's purchases from the main supplier to the firm's sales. The coefficient on the interaction term in Model 4 (*Lagged Main Supplier R&D*Supplier Importance*) is positive (0.061), albeit insignificant at conventional levels ($t = 1.55$).

Model 5 of Table 3 presents the coefficients on the predicted R&D of the firm's main supplier from the 2SLS regression model. To conserve space, we list in the legend of Table 3 the variables used in the first stage as instruments to estimate the predicted values of *Main Supplier R&D*. All the variables are winsorized at the 1st and 99th percentiles. Our choice of control variables for the first stage in the 2SLS regression model is motivated by prior research in accounting and finance on the determinants of R&D spending (see, e.g., Darrough and Rangan 2005 and Coles et al. 2006).

The estimates from the 2SLS model are presented in Model 5 of Table 3. The coefficient on *Main Supplier R&D* is equal to 0.031 (significant at the 10 percent level). This finding is consistent with the results based on lagged values of the R&D variables and further suggests that our results are not driven by endogeneity. Overall, the results reported in Table 3 are consistent with H1 and reinforce the results based on the industry-level variables presented in Table 2.

The results pertaining to the key customers' variables are reported in Table 4, which is modeled after Table 3. In contrast to the results for the key supplier variables, the coefficients on the customer variables are negative and significant in all the models reported in Table 4. The contrasting findings for the effects of customer R&D on firms' earnings management suggests that factors other than the incentive to report favorable performance influence the earnings management decisions of supplier firms. One such factor discussed in the literature is the role of bargaining power, which we examine below.

Prior research suggests that large customers, by exercising their buyer power, can pressure their profitable suppliers and extract price concessions (e.g., Schumacher 1991; Snyder 1996).[20] Similarly, large suppliers could have greater seller power over their smaller customers. Further, Bowen et al. (1995) hypothesize that firms engaged in ongoing contract negotiations with labor unions have fewer incentives to choose income-increasing accounting methods, and find supportive evidence. In a similar vein, firms engaged in negotiations with suppliers and customers over the terms of transactions could have disincentives to use income-increasing accruals, especially when they are at a bargaining disadvantage. As such, the effects of customer R&D on firms' earnings management depend on the net impact of the incentive to report favorable prospects and the incentive to hide high levels of profitability from the customer.

---

[19] We test whether the relations between the supplier variables and *Earnings Management* are more pronounced for financially weak firms. In untabulated results, we find that the coefficients on *Lagged Key Suppliers R&D*Zscore Dummy* and *Lagged Main Supplier R&D*Zscore Dummy* are both positive, with the former being statistically significant at conventional levels. The coefficient on *Supplier Alliance and JV Dummy*Zscore Dummy* is statistically insignificant (t-statistic = −0.8). These results are, on balance, in line with our earlier findings.

[20] The business press also recognizes the ability of customers to expropriate wealth from their profitable suppliers. For example, Fitzgerald (1996) suggests that suppliers of U.S. automakers resist opening their books to customers because a large customer could chip away at their profit margins.

We conduct additional analyses, presented in Table 5, to examine whether the relation between the (lagged) R&D for the main supplier or customer and *Earnings Management* depends on the firm's bargaining power *vis-à-vis* its suppliers/customers. We use the firm's size relative to that of the supplier/customer as a proxy for the firm's bargaining power.[21]

Model 1 (Model 2) of Table 5 presents regression results with the firm's earnings management as the dependent variable, and the interaction between the firm's size relative to that of the main supplier (customer) and the lagged R&D of the main supplier (customer) as the independent variables of interest. The bargaining argument predicts a positive coefficient on the interaction terms. The results indicate that the supplier's R&D is positively related to the firm's earnings management regardless of the firm's relative size. In contrast, the interaction term is positive and significant in Model 2, indicating that the effect of customers' relationship-specific investments on firms' earnings management is less negative when firm size (relative to that of customers) is larger. The magnitude of the coefficients on the two variables, (lagged) *Main Customer R&D* and (lagged) *Main Customer R&D*Firm Relative Size*, indicate that the relation between (lagged) *Main Customer R&D* and firm's earnings management is positive when *Firm Relative Size* is greater than 1, that is, when the firm is larger than its customer. These findings support the reasoning that the weak bargaining power of firms *vis-à-vis* their customers leads to lower earnings management.

Relationship-Specific Investments and Income Smoothing

One issue arising from the previous results is whether the use of accounting discretion in the presence of relationship-specific investments is aimed at smoothing or inflating income. On one hand, if firms smooth earnings to influence suppliers/customers, we expect the volatility of reported earnings to be less than that of cash flows. On the other hand, if firms use income-increasing accruals to influence suppliers/customers by inflating earnings, we expect firms whose suppliers/customers invest more in relationship-specific assets to have higher earnings volatility (relative to cash flow volatility). To examine this issue, we regress measures of income smoothing on the proxies for relationship-specific investments.

Following Subramanyam (1996) and Leuz et al. (2003), we use two different measures of income smoothing. First, we use *Volatility Ratio*, defined as the ratio of the standard deviation of net income (NI) to the standard deviation of operating cash flow (OCF). We require that both NI and OCF have at least five consecutive observations. In the first two columns of Table 6, we report results from a regression of *Volatility Ratio* on the supplier and customer variables. Since for each firm we have only one value for *Volatility Ratio*, we use the mean values of explanatory variables in the regressions. While we report results using industry-level supplier and customer variables, the results using subsamples with key supplier and customer data are in the same direction, with some of the results statistically insignificant probably due to the small sample size. The results indicate that, except for *Supplier Alliance and JV Intensity*, the supplier and customer variables are positively related to *Volatility Ratio*. For instance, changing the value of *Supplier Industries R&D*

---

[21] The use of the firm's absolute size or market share in its primary industry as a measure of its bargaining power yields similar results.

TABLE 5

Regression Analysis of Absolute Value of Discretionary Accruals Conditional on Relative Size

	Model 1	**Model 2**
Intercept	0.077***	0.175***
	(2.75)	(5.74)
Supplier Variables		
Lagged Main Supplier R&D	0.021**	
	(2.13)	
*Lagged Main Supplier R&D * Firm Relative Size*	0.001	
	(0.25)	
Firm Relative Size	0.000	
	(0.30)	
Customer Variables		
Lagged Main Customer R&D		−0.151***
		(−2.70)
*Lagged Main Customer R&D * Firm Relative Size*		0.151**
		(2.22)
Firm Relative Size		0.002
		(0.26)
Control Variables		
Firm R&D Intensity	0.067*	0.023
	(1.94)	(1.60)
Firm Advertising Intensity	0.014	0.092***
	(0.56)	(2.73)
Human-Capital Intensity	0.015***	0.020***
	(4.20)	(6.32)
Leverage	0.003	0.016***
	(0.43)	(3.21)
Firm Size	−0.003***	−0.008***
	(−4.55)	(−8.66)
Firm Age	−0.003***	0.000***
	(−4.46)	(−4.64)
Book-to-Market	−0.006	−0.032***
	(−1.33)	(−11.08)
Return on Assets	−0.050***	−0.046***
	(−2.60)	(−6.86)
Free Cash Flow Dummy	0.007	0.006*
	(1.47)	(1.73)
Operating Cash Flow	0.086***	0.013
	(4.37)	(1.55)

(continued on next page)

TABLE 5 (continued)

	Model 1	Model 2
Sales Growth	0.020***	0.016***
	(4.53)	(8.98)
Volatility of Cash Flows	0.075***	−0.001
	(2.65)	(−0.12)
Volatility of Net Income	0.024	−0.003
	(1.39)	(−0.99)
Volatility of Sales	0.024***	0.031***
	(4.07)	(6.20)
Year and Industry Indicators	Yes	Yes
Number of Observations	5,533	13,100
Adjusted R^2	19.95%	16.01%

*, **, *** Indicate statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively.

The dependent variable is *Earnings Management*, which is the absolute value of discretionary accruals. *Lagged Main (Supplier) Customer R&D* is the lagged value of the R&D of main customer (supplier), normalized by total assets. *Firm Relative Size* in Model 1 (Model 2) is the natural log of the customer's (supplier's) total assets divided by the natural log of the total assets of the main supplier (customer). The control variables are described in Table 1. The coefficient on *Firm Age* is multiplied by 10. The reported t-values are based on heteroscedasticity robust standard errors adjusted for clustering at the firm level.

(*Customer Industries R&D*) from the 5th to the 95th percentile results in a 0.20 (0.28) change in *Volatility Ratio*, which has a median value of 1.07.

Second, we use *Correlation*, defined as the correlation between changes in total accruals and changes in operating cash flow, as a measure of income smoothing (see, e.g., Subramanyam 1996). The reversal of accruals dictated by the accounting process leads to a negative correlation between the change in total accruals and change in cash flows. A more negative correlation would therefore indicate that the earnings stream is smoother than it would be in the absence of discretionary accruals.

The results in the third and fourth columns of Table 6 indicate that the coefficients on supplier and customer variables, with the exception of *Supplier Alliance and JV Intensity*, are positive and significant in regressions with *Correlation* as the dependent variable. These results, like those in the first two columns, indicate that firms with relationship-specific investments by suppliers and customers exhibit greater volatility in reported earnings.[22] One factor contributing to the higher volatility could be the incentive for firms to report higher earnings, which we examine below.

Are Relationship-Specific Investments Associated with Higher Reported Earnings?

One motivation for using large discretionary accruals, suggested by Bowen et al. (1995) and Burgstahler and Dichev (1997), is that firms can inflate their reported earnings and favorably

---

[22] We also interact the supplier/customer variables with *Zscore Dummy*. In untabulated results, we find that in regressions pertaining to *Volatility Ratio (Correlation)*, two (one) of the four interaction variables are (is) positive and significant, while the coefficients on the other interaction terms are mostly positive, although statistically insignificant at conventional levels.

TABLE 6

Regression Analysis of the Smoothing Variables

	Ratio		Correlation	
Intercept	0.874***	0.975***	−0.595***	−0.574***
	(7.01)	(7.87)	(−16.07)	(−15.58)
Supplier Variables				
Supplier Industries R&D	10.207***		1.822*	
	(2.75)		(1.85)	
Supplier Alliance and JV Intensity		−0.022		0.014
		(−0.37)		(0.83)
Customer Variables				
Customer Industries R&D	5.584***		1.633***	
	(3.47)		(3.83)	
Customer Alliance and JV Intensity		0.289***		0.075***
		(4.63)		(4.13)
Control Variables				
Firm R&D Intensity	1.645***	1.874***	0.583***	0.623***
	(6.96)	(8.12)	(7.87)	(8.60)
Firm Advertising Intensity	−0.233	−0.368	0.110	0.068
	(−0.46)	(−0.72)	(0.73)	(0.46)
Human-Capital Intensity	0.227***	0.235***	0.012	0.013
	(4.20)	(4.37)	(0.79)	(0.84)
Leverage	0.641***	0.612***	0.114***	0.109***
	(8.75)	(8.37)	(5.19)	(4.99)
Firm Size	0.006	0.007	0.004	0.003
	(0.64)	(0.71)	(1.45)	(1.29)
Firm Age	−0.012***	−0.013***	−0.001**	−0.001***
	(−6.82)	(−7.33)	(−2.41)	(−2.73)
Book-to-Market	0.168***	0.156**	0.028	0.027
	(2.75)	(2.56)	(1.58)	(1.50)
Return on Assets	−2.570***	−2.593***	−0.285***	−0.288***
	(−20.61)	(−20.77)	(−6.56)	(−6.64)
Free Cash Flow Dummy	0.722***	0.720***	0.109***	0.107***
	(8.76)	(8.72)	(4.26)	(4.20)
Operating Cash Flow	2.603***	2.648***	0.144**	0.150**
	(14.97)	(15.23)	(2.43)	(2.54)
Sales Growth	−0.217***	−0.220***	0.021*	0.022*
	(−6.03)	(−6.11)	(1.79)	(1.85)
Volatility of Cash Flows	0.396***	0.399***	−0.036*	−0.037*
	(9.65)	(9.69)	(−1.83)	(−1.89)
Volatility of Net Income			0.017**	0.017**
			(2.18)	(2.22)

(continued on next page)

TABLE 6 (continued)

	Ratio		Correlation	
Volatility of Sales			0.042*** (3.38)	0.041*** (3.28)
Industry Indicators	Yes	Yes	Yes	Yes
Number of Observations	9,051	9,051	7,975	7,975
Adjusted R^2	16.11%	15.87%	11.31%	11.24%

*, **, *** Indicate statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively.

Columns 1 and 2 of this table show results of OLS regressions of the ratio of the standard deviation of net income to the standard deviation of operating cash flow. Columns 3 and 4 show results of OLS regressions of the Spearman correlation coefficient between the change in total accruals and change in cash flow from operations. *Supplier (Customer) Industries R&D* is the weighted average of the R&D intensities of all supplier (customer) industries. *Supplier (Customer) Alliance and JV Intensity* is the number of strategic alliances and joint ventures established between industry firms and firms in supplier (customer) industries, divided by the number of firms in the industry. The control variables are described in Table 1. The time-series means of the control variables are used. The coefficient on *Firm Age* is multiplied by 10. The t-values reported in parenthesis reflect White's (1980) heteroscedasticity correction.

influence stakeholder perceptions of future revenues from the business relationship.[23] When suppliers/customers invest in relationship-specific assets, large positive earnings changes reported by the firm are likely to increase the perceived revenues from the transaction. We test this hypothesis by providing evidence on whether relationship-specific investments by suppliers/customers influence the frequency with which firms report large earnings increases. To detect whether the large earnings changes can be attributed to the use of discretionary accruals, we control for the frequency with which firms report large changes in the operating cash flow.

In both regression models presented in Table 7, the dependent variable is *FreqLarge*, defined as the frequency of earnings changes in the 90th percentile of the distribution of earnings changes across all firm-year observations.[24] Earnings change is computed using earnings before extraordinary items (item 18) and normalized by lagged total assets. The distribution of earnings change is centered on a median of 0.006 with a mean of 0.013. The observations at or above the 90th percentile value of 0.180 thus represent large earnings increases.

The results provide evidence of a strong link between relationship-specific investments by suppliers/customers and the frequency of large earnings increases reported by firms. The coefficients on the four supplier and customer variables *Supplier Industries R&D*, *Supplier Alliance and JV Intensity*, *Customer Industries R&D*, and *Customer Alliance and JV Intensity* are all positive and statistically significant. We find that moving from the 5th to the 95th percentile value of *Supplier Industries R&D* (*Customer Industries R&D*) results in a 0.04 (0.02) change in *FreqLarge*, which has a median value of 0.06. These results are consistent with firms using

---

[23] Prior studies focusing on event-specific earnings management suggest that firms have incentives to inflate earnings prior to corporate events (e.g., Rangan 1998; Teoh et al. 1998; Shivakumar 2000).

[24] In the construction of *FreqLarge*, we follow Bowen et al. (2005) who construct a similar variable to analyze the frequency of small earnings surprises.

TABLE 7

Regression Analysis of the Frequency of Large Increases in Earnings

	Dependent Variable is *FreqLarge*	
Intercept	0.067***	0.079***
	(7.60)	(9.01)
Supplier Variables		
Supplier Industries R&D	1.813***	
	(6.96)	
Supplier Alliance and JV Intensity		0.007*
		(1.73)
Customer Variables		
Customer Industries R&D	0.365***	
	(3.20)	
Customer Alliance and JV Intensity		0.033***
		(7.57)
Control Variables		
Frequency of Large Cash Flow	0.374***	0.375***
	(37.84)	(37.85)
Firm R&D Intensity	0.100***	0.132***
	(6.03)	(8.10)
Firm Advertising Intensity	0.168***	0.158***
	(4.63)	(4.35)
Human-Capital Intensity	−0.008**	−0.006
	(−2.20)	(−1.64)
Leverage	0.012**	0.009*
	(2.36)	(1.74)
Firm Size	−0.009***	−0.009***
	(−13.35)	(−13.48)
Firm Age	−0.003**	−0.003***
	(−2.24)	(−2.90)
Book-to-Market	−0.026***	−0.027***
	(−5.99)	(−6.29)
Return on Assets	−0.046***	−0.049***
	(−5.13)	(−5.42)
Free Cash Flow Dummy	0.043***	0.043***
	(8.00)	(8.00)
Operating Cash Flow	−0.021	−0.014
	(−1.61)	(−1.09)
Sales Growth	0.003	0.003
	(1.26)	(1.12)
Volatility of Cash Flows	−0.017***	−0.017***
	(−3.50)	(−3.60)

(continued on next page)

TABLE 7 (continued)

	Dependent Variable is *FreqLarge*	
Volatility of Net Income	0.008***	0.008***
	(4.14)	(4.31)
Volatility of Sales	0.033***	0.033***
	(11.15)	(10.95)
Industry Indicators	Yes	Yes
Number of Observations	9,112	9,112
Adjusted R^2	51.03%	51.70%

*, **, *** Indicate statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively.

This table shows results of OLS regressions of *FreqLarge*, defined as the frequency of earnings changes in the 90th percentile of the distribution of *Earnings Change*, which is earnings before extraordinary items minus its lagged value, normalized by lagged total assets. *Supplier (Customer) Industries R&D* is the weighted average of the R&D intensities of all supplier (customer) industries. *Supplier (Customer) Alliance and JV Intensity* is the number of strategic alliances and joint ventures established between industry firms and firms in supplier (customer) industries, divided by the number of firms in the industry. *Frequency of Large Cash Flow* is the frequency of operating cash flow changes in the 90th percentile of the distribution of *CFO Change*, which is cash flow from operations minus its lagged value, normalized by lagged total assets. The control variables are described in Table 1. The time-series means of the control variables are used. The coefficient on *Firm Age* is multiplied by 10. The t-values reported in parenthesis reflect White's (1980) heteroscedasticity correction.

accounting discretion to report large earnings increases more frequently when suppliers/customers invest in relationship-specific assets.[25]

In untabulated results, we find that the coefficients on *Supplier Industries R&D*Zscore Dummy and Supplier Alliance* and *JV Intensity*Zscore Dummy* are positive and statistically significant. The customer-related interactions are statistically insignificant. Among the control variables, we find that *Firm R&D Intensity, Firm Advertising Intensity*, and *Leverage* are positively and significantly related to the tendency for firms to report large earnings increases. These results are in line with the findings in Bowen et al. (1995).

Consequences of Firm's Earnings Management on Supplier/Customer Relationships

Effect of Earnings Management on Supplier/Customer R&D Investments

Taken as a whole, the above results provide evidence of a higher magnitude of firm's earnings management when the firm deals with suppliers and customers who are likely to undertake relationship-specific investments. One issue arising from these findings is whether a firm's earnings management in one period affects the magnitude of relationship-specific investments by its suppliers and customers in the next period. We examine this issue by analyzing the intertemporal relation between firms' earnings management and the level of R&D investments by suppliers and customers.

---

[25] Note that although *FreqLarge* is a *change-based* variable, we use the *level* of our independent variables in the regression analysis. We focus on the level of (rather than the change in) relationship-specific investments by customers/suppliers during the time period to capture the type of environments in which firms operate. Specifically, our cross-sectional test is designed to examine whether firms report large earnings changes more frequently in environments characterized by high relationship-specific investments by customers/suppliers.

For the purpose of this intertemporal analysis, we include a supplier-customer pair for year t only if the supplier and customer are linked in the Compustat segment files in year $t-1$. The regression results are presented in Table 8. In the first two columns, the dependent variable is supplier R&D with the lagged (signed) discretionary accruals of the main customer as the independent variable of interest. Similarly, in the last two columns, the dependent variable is the customer R&D with the lagged discretionary accruals of the main supplier as the independent variable of interest. Recall that we define the control variables for the R&D regressions in the legend of Table 3. To capture the marginal effect of discretionary accruals on R&D, we include the nondiscretionary component of earnings (*Pre-Discretionary Income*) as an additional control variable in the regressions, which is equal to *Return on Assets* (as defined earlier) minus discretionary accruals.[26] In addition, we include an interaction term to examine how the importance of customers (suppliers) to suppliers (customers) influences the effect of earnings management on R&D investments. For instance, a customer's earnings management is likely to affect the supplier's R&D only if the customer is important to the supplier.

As shown in the second column of Table 8, the coefficient on the interaction term is positive and significant with a t-statistic of 2.13. This result indicates that the effect of the customer's discretionary accruals in one period on the supplier's R&D investment in the next period is positive and significant when the customer's purchases from the supplier are high. For instance, for a supplier with a median value of *Customer Importance*, a one standard deviation change in the customer's discretionary accruals results in an increase in the supplier R&D to asset ratio by 0.003, compared to a median value of 0.007. In the last two columns, we find that, although the coefficient on the supplier's discretionary accruals is not significant in explaining the customer's R&D, the coefficient on the interaction term is equal to 0.182, with a t-statistic of 2.03. These results suggest that the effect of earnings management on relationship-specific investments by suppliers and customers is pronounced when the relationship between the firm and these stakeholders is more important. The results also suggest that suppliers and customers are unable to fully anticipate the extent of earnings management by the firm.

There is evidence in the literature that firms use R&D spending as an earnings management device (e.g., Baber et al. 1991; Bushee 1998; Darrough and Rangan 2005). Because R&D spending can be affected by factors influencing the propensity for earnings management, we include the controls used in the earnings management regressions (as in Table 3 and 4) as controls in regressions using R&D spending as the dependent variable (in Table 8). The untabulated results from this extended model are similar to those reported in the Table 8.

The evidence pertaining to *Pre-Discretionary Income* suggests that firms undertake more R&D investments when their suppliers/customers have higher pre-discretionary earnings, and this effect is more pronounced when the customer/supplier is more important to the firm's operations. The results related to the control variables are largely consistent with the literature. For instance, the coefficients on *Cash* and *Operating Cash Flow Surplus* are positive, while the coefficients on

---

[26] *Returns on Assets* is the sum of net income before extraordinary items (data 18) and R&D expense (data 46) divided by total assets. For the purpose of our earlier analysis in Tables 3–5, we add back R&D expense to net income since we control for R&D intensity in our regressions. In this part of the analysis, we use the same definition (that is, we add back R&D to net income) to account for a mechanical negative correlation between supplier R&D and customer's net income (net of R&D spending), resulting from a positive correlation between the supplier and the customer R&D investments.

TABLE 8

Regression Analysis of R&D of Suppliers and Customers

	Supplier R&D		Customer R&D	
Intercept	−0.024	−0.036	0.007	0.002
	(−1.54)	(−2.34)	(0.87)	(0.21)
Customer Variables				
Lagged Customer Discretionary Accruals	0.030	−0.040		
	(1.38)	(−1.17)		
*Lagged Customer Discretionary Accruals * Customer Importance*		0.273**		
		(2.13)		
Lagged Customer Pre-Discretionary Income	0.028*	−0.025		
	(1.90)	(−0.96)		
*Lagged Customer Pre-Discretionary Income * Customer Importance*		0.206***		
		(3.21)		
Customer Importance		0.025**		
		(2.45)		
Supplier Variables				
Lagged Supplier Discretionary Accruals			0.007	0.003
			(1.14)	(0.44)
*Lagged Supplier Discretionary Accruals * Supplier Importance*				0.182**
				(2.03)
Lagged Supplier Pre-Discretionary Income			−0.001	−0.004
			(−0.26)	(−1.03)
*Lagged Supplier Pre-Discretionary Income * Supplier Importance*				0.101*
				(1.82)
Supplier Importance				0.046***
				(3.56)
Control Variables				
Size	−0.001	0.000	−0.001	−0.001
	(−0.94)	(0.11)	(−1.09)	(−0.74)
Book-to-Market	−0.013***	−0.011***	−0.003	−0.003
	(−2.88)	(−2.58)	(−0.71)	(−0.70)
Sales Growth	−0.001	−0.001	0.000	−0.001
	(−0.22)	(−0.28)	(−0.05)	(−0.25)
Stock Return	−0.010***	−0.010***	−0.002	−0.001
	(−5.72)	(−5.85)	(−0.91)	(−0.76)
Leverage	0.026***	0.026***	−0.002	−0.002
	(3.56)	(3.53)	(−0.34)	(−0.30)
Operating Cash Flow Surplus	0.061***	0.063***	0.066***	0.068***
	(3.88)	(4.01)	(3.38)	(3.59)
Financing Cash Flow	0.104***	0.103***	0.051***	0.049***
	(7.32)	(7.31)	(3.68)	(3.37)

(continued on next page)

TABLE 8 (continued)

	Supplier R&D		Customer R&D	
Cash	0.099***	0.093***	0.043**	0.040**
	(7.28)	(6.99)	(2.50)	(2.53)
Capital Expenditures	0.022	0.015	−0.044**	−0.043**
	(0.97)	(0.64)	(−2.28)	(−2.20)
SGA Expenses	0.106***	0.111***	0.024***	0.026***
	(8.28)	(8.42)	(2.60)	(3.26)
Industry R&D	0.975***	0.966***	0.996***	0.995***
	(14.20)	(14.58)	(18.52)	(18.87)
Year and Industry Dummy Variables	Yes	Yes	Yes	Yes
Number of Observations	6,782	6,782	2,615	2,615
Adjusted R^2	53.91%	54.43%	69.93%	66.22%

*, **, *** Indicate statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively.

This table reports results of regression analysis of the R&D of suppliers (customers) on the lagged values of the earnings management variables for the main customer (supplier). *Lagged Customer (Supplier) Discretionary Accruals* is the lagged signed value of the customer (supplier) discretionary accruals. *Lagged Customer (Supplier) Pre-Discretionary Income* is the lagged customer (supplier) net income plus R&D (normalized by total assets) minus discretionary accruals. *Customer Importance* is the percentage of the supplier sales made to the customer. *Supplier Importance* is the dollar purchases from the supplier divided by the customer total sales. *Size* is the log of the total assets. *Book-to-Market* is the total assets divided by the sum of the book value of debt and market value of common equity. *Sales Growth* is the one-year growth in total sales. *Stock Return* is the one-year stock return. *Leverage* is the book value of long-term debt and debt in current liabilities divided by the book value of assets. *Operating Cash Flow Surplus* is cash from assets-in-place divided by total assets. *Financing Cash Flow* is cash flow from financing activities. *Cash* is cash normalized by total assets. *Capital Expenditures* is capital expenditures normalized by total assets. *SGA Expenses* is selling, general, and administrative expenses normalized by total assets. *Industry R&D* is the sum of R&D of industry firms normalized by the sum of total industry assets. The reported t-values are based on heteroscedasticity robust standard errors adjusted for clustering at the firm level.

Book-to-Market and *Stock Return* are negative, consistent with the findings in Darrough and Rangan (2005) and Coles et al. (2006).[27]

Earnings Management and Supplier/Customer R&D: Discussion of Results

The overall results on the effect of earnings management on supplier/customer R&D investments suggest that although a supplier influences the customer's investment behavior through earnings management, its own investment behavior is influenced by the customer's earnings management. Can this finding be explained within a rational expectations framework? Based on rational expectations, a pooling equilibrium may exist such that "bad-quality" suppliers manage earnings to pool with "good-quality" suppliers and affect the customer's relationship-specific investments. Such a pooling outcome is also possible on the customer side of the market.[28] However, as abnormal accruals can be estimated prior to suppliers and customers entering into relationships, under rational expectations, suppliers (customers) would use the information contained in abnormal accruals to form unbiased expectations about the probability of a given customer (supplier) being of the good or bad type. If so, then one should not find that, on average, greater earnings management leads to higher investments by suppliers/customers.

---

[27] We note that *Lagged Customer (Supplier) Discretionary Accruals and Lagged Customer (Supplier) Pre-Discretionary Income* are negatively correlated. This negative correlation can be the result of income smoothing (Subramanyam, 1996) or can be mechanical due to the measurement error in the estimate of discretionary accruals. To check whether this negative correlation results in a multicollinearity problem, we examine the regressions' Variance Inflation Factors (VIF). We find that none of the VIF values exceeds the critical value of 10; most of these values are below 2 and some are close to 4 only when we include interaction terms (columns 2 and 4 of Table 8).

Alternatively, the findings suggest that managers of supplier firms appear to be fixated on the earnings reported by customer firms (and *vice versa*), and thereby fail to fully distinguish between the cash flow and accrual components of earnings. This explanation is consistent with the earnings fixation hypothesis in Sloan (1996), according to which stakeholders such as investors do not fully undo firms' earnings management. The notion that firms can influence suppliers/customers' investment behavior through earnings management is also consistent with the findings of Bowen et al. (1995), which suggest that managers choose income-increasing accounting methods to influence the perception (and therefore, the actions) of some stakeholders.

Earnings Management and the Duration of Supplier-Customer Relationships

In this section, we examine whether earnings management affects the incentives of suppliers and customers to continue the business relationship. We test H2 (ii) by examining regression results from analyses of the relationship duration. The results of the duration analysis, presented in Table 9, are based on three different models to verify the robustness of our conclusions (see Allison 1995). The first model we use is an accelerated failure time (AFT) model. In this model the dependent variable is the length (in years) of the relationship for each supplier-customer pair and is assumed to follow a Weibull distribution.[29] In the Weibull model, the probability of surviving beyond a specific point in time is assumed to depend on a set of explanatory variables. In addition to the earnings management variables, which are the variables of interest, we follow Fee et al. (2006) and use a set of control variables that are described in Table 9. We use the average values of *Earnings Management* for customers and suppliers during the period covering their relationship. As shown in the first column of Table 9, the coefficients on *Supplier Earnings Management* and *Customer Earnings Management* are both negative. These results indicate that higher values of *Supplier Earnings Management* or *Customer Earnings Management* are associated with shorter relationships.

Next, we estimate a Cox proportional hazards model.[30] This model, proposed by Cox (1972), is a generalization of the Weibull model in that the baseline hazard function in the Cox model can take any form without being restricted by the assumption of a specified distribution. As a result,

---

[28] The sustainability of such equilibrium depends on the cost of signals that good-quality suppliers can use to separate themselves, such as the use of a reputable auditor or use of conservative accounting. While outsiders may rely on auditor reputation to distinguish between firm types, both audit effort and quality can suffer from conflicts of interest due to nonaudit services (Simunic 1984; Bradshaw et al. 2001; Frankel et al. 2002; Caramanis and Lennox 2008). Additionally, Lizzeri (1999) predicts that intermediaries may optimally disclose only whether the quality of information is above some minimum standard so as to generate additional rents from clients who would otherwise not choose the auditor. Thus, incentive problems could preclude reputed auditors from perfectly separating firms that manage earnings from those that do not.

[29] To calculate the length of the relationship, we assume that the beginning year is the year when the relationship first appears in our segment data set and the ending year is the year when the relationship disappears from the data set. We only include relationships that start in 1985 since we cannot determine the start of relationships that first appear in 1984, the first year in our sample. In addition, we treat as right censored all relationships that last until the last year of the sample (2002) and those that disappear if the coverage for either the supplier or customer stops in Compustat.

[30] In the context of our study, hazard refers to the probability that a firm will experience an event (in this case, termination of relationship with its supplier or customer) within an interval of time, given that the relationship has survived up to the beginning of the interval. Moreover, "proportional hazards" refers to the assumption in the model that the hazard for any firm is a fixed proportion of the hazard for any other firm, and does not vary with time.

TABLE 9

Duration Analysis

	(1) Weibull Model	(2) Cox PHM Model		(3) Logit Model
	Coefficient (Chi-Square)	**Coefficient (Chi-Square)**	**Hazard Ratio**	**Coefficient (Chi-Square)**
Intercept	1.160***	NA	NA	0.267
	(107.49)			(3.66)
Earnings Management Variables				
Supplier Earnings Management	−1.135***	0.738***	2.09	0.4821**
	(31.67)	(9.74)		(5.35)
Customer Earnings Management	−1.247***	0.977**	2.66	0.256
	(10.70)	(4.99)		(0.41)
Control Variables				
Customer Importance	0.727***	−0.769***	0.46	−2.939***
	(36.46)	(27.75)		(287.31)
Supplier Importance	−0.007	0.006	1.01	0.039
	(0.33)	(0.18)		(2.31)
Supplier Size	0.083***	−0.098***	0.91	−0.139***
	(54.65)	(52.19)		(99.83)
Customer Size	0.040***	−0.039***	0.96	−0.070***
	(11.32)	(7.56)		(20.67)
Supplier Age	0.006***	−0.005**	1.00	−0.009***
	(8.94)	(4.44)		(12.05)
Customer Age	−0.003*	0.004**	1.00	0.002
	(2.74)	(4.92)		(0.70)
Supplier Free Cash Flow Dummy	−0.189***	0.144***	1.15	0.392***
	(25.13)	(9.58)		(68.57)
Customer Free Cash Flow Dummy	0.003	−0.037	0.96	0.128***
	(0.01)	(0.55)		(6.35)
Supplier R&D Intensity	−0.311**	0.184	1.20	1.237***
	(4.82)	(1.15)		(39.72)
Customer R&D Intensity	−1.292***	1.288***	3.63	2.072***
	(17.90)	(12.45)		(23.79)
Tenure				−0.055***
				(33.44)
Number of Observations	3,668	3,668		11,662
Log Likelihood	−4,041.24	—		—
Overall Chi-Square	—	202.01		915.77

(continued on next page)

TABLE 9 (continued)

---

*, **, *** Indicate statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively.

This table reports results of regression analyses of the relationship duration. Column 1 (Column 2) reports estimates from a Weibull model (Cox proportional hazards model or PHM) in which the dependent variable is the length (in years) of the customer-supplier relationship. In both the Weibull and Cox models, each relationship is treated as a single observation. Relationships that are first observed in 1984 are excluded from the sample. Relationships that continue until the end of the sample period (2002) or those where either the supplier or the customer becomes inactive in Compustat are treated as right-censored. Column 3 reports estimates from a Logit model where the dependent variable is set equal to 1 if a relationship ends in the subsequent year, and 0 otherwise. *Supplier (Customer) Earnings Management* is the absolute value of discretionary accruals of the supplier (customer) firm estimated using the modified Jones model as in Equations (7) and (8). In the Weibull and Cox models, the averages of the supplier and customer earnings management variables over the duration of the relationship are used. The control variables are as follows: *Customer Importance* is the percentage of the supplier sales made to the customer. *Supplier Importance* is the dollar purchases from the supplier divided by the customer total sales. *Supplier (Customer) Size* is the log the supplier (customer) assets. *Supplier (Customer) Age* is the number of years in which the supplier (customer) is listed on Compustat. *Supplier (Customer) Free Cash Flow Dummy* is a dummy variable that equals 1 if the supplier (customer) free cash flow is negative, and 0 otherwise. *Supplier (Customer) R&D Intensity* is the ratio of the supplier (customer) R&D expense to total assets. *Tenure* is the number of years the relationship has been in existence as of the start of the observation year. In the Weibull and Cox models, the values of the independent variables are set equal to their values in the first year of the relationship. A negative (positive) coefficient in column 1 (2 and 3) suggests that an increase in the independent variable results in a shorter relationship duration.

the Cox model is more robust than the Weibull model (Allison 1995). In this model, the hazard of termination of a relationship is assumed to depend on the same set of explanatory variables. Since the estimation of this model is based on the hazard function, a positive coefficient for a given explanatory variable implies that an increase in this variable results in shorter relationship length. The estimates from this model are reported in Column 2 of Table 9 and are consistent with our earlier results. The coefficients on the earnings management variables are both positive and statistically significant, suggesting that higher magnitude of discretionary accruals is associated with shorter relationships. Examining the economic significance of these coefficients, we find that moving the *Supplier (Customer) Earnings Management* from the 5th to the 95th percentile results in an increase in the hazard of relationship termination by about 33.39 percent (25.23 percent).[31]

Finally, we estimate a logistic regression model where the dependent variable equals 1 if the relationship ends in the subsequent year, and 0 otherwise. In contrast to the AFT and Cox models, where the relationship duration is measured in years as a continuous variable, in the logistic model we treat relationship termination as a discrete variable for each year in the sample. Consistent with the results in the first two models, we find that the coefficients on both supplier and customer earnings management variables are positive although the customer variable is not significant based on the Chi-squared statistic.

---

[31] To compute the percent change in the hazard of termination for a one-unit change in earnings management, we subtract 1 from the hazard ratio and multiply by 100 (see Allison 1995, 117).

The sign and significance of the coefficients on control variables are broadly consistent with those reported in prior studies (e.g., Fee et al. 2006). For instance, relationships with longer tenure and those involving large and older suppliers are less likely to terminate sooner. In addition, higher levels of supplier R&D intensity increase the likelihood of relationship termination, consistent with the findings in Fee et al. (2006).

Overall, the findings in this section are consistent with the view that the duration of supplier-customer relationships is shorter when firms use large magnitudes of discretionary accruals. Given that termination of relationships entails costs for firms and their suppliers/customers, the findings highlight a potential cost associated with earnings management.

Robustness Checks

Discretionary accruals are often measured with noise (e.g., Dechow and Dichev 2002; Kothari et al. 2005). To check the robustness of our results from tests based on discretionary accruals, we repeat our analysis using different models to estimate discretionary accruals. The findings from these models are consistent with the reported results. The alternative specifications are as follows:

(1) The use of the modified Jones model without including controls for performance and growth (ROA and BM in Equation (7)).
(2) The use of pooled time-series cross-sectional regressions to estimate the nondiscretionary accrual model (Equation (7)).
(3) The inclusion of an intercept term in the nondiscretionary accrual model (Equation (7)) (see Kothari et al. 2005).
(4) The inclusion of change in cash flow normalized by lagged assets as an independent variable in the nondiscretionary accrual model (Equation (7)) (see Bowen et al. 2005).
(5) The use of the nonlinear accrual model developed by Ball and Shivakumar (2006).
(6) The use of the Hribar and Collins (2002) measure of total accruals (net income minus operating cash flow) in Equation (7).

The estimation of the model in Equation (7) for each year and four-digit SIC code industry. We also estimate discretionary accruals using the Dechow and Dichev approach as applied by Aboody et al. (2005) and Francis et al. (2005). The details of these models are:

(7) Based on Aboody et al. (2005), we estimate discretionary accruals using the following model (all variables scaled by the average assets over years t and $t-1$):

$$TCA_{j,t} = b_1 + b_2 CFO_{j,t-1} + b_3 CFO_{j,t} + b_4 CFO_{j,t+1} + v_{j,t} \tag{9}$$

where *TCA* is total current accruals and CFO is cash flow from operations (see Aboody et al. [2005] for more details). The model is estimated for each year and two-digit SIC code industry with at least 20 firms.

(8) Following Francis et al. (2005), we estimate discretionary accruals using a modified Dechow and Dichev (2002) model, which is constructed by adding to Equation (9) the change in revenues and property, plant, and equipment, both scaled by average assets. The model is estimated for each year and two-digit SIC code with at least 20 firms.

V. CONCLUSION

Suppliers and customers are interested in the firm's future prospects as their profitability depends on transactions with the firm. In particular, the value of relationship-specific investments by corporate suppliers and customers depends on the future prospects of their relationship with the firm. In addition, suppliers and customers investing in relationship-specific assets are susceptible to *ex post* expropriation of rents because such assets have lower value outside their relationship with the firm. Consequently, a firm's incentive to extract rents affects the *ex ante* incentives of suppliers/customers to invest in relationship-specific assets. Since the perceptions of suppliers and customers about the firm's incentives are influenced by the firm's financial condition, firms can benefit from projecting a good financial image.

We test hypotheses regarding supplier- and customer-related motives for earnings management using two different data sets. Using the input-output accounts, we identify supplier/customer industries for each four-digit SIC code industry in our sample. We then use R&D intensities of supplier/customer industries, and the intensity of alliances and joint ventures (JVs) among firms in supplier and customer industries, as measures of relationship-specific investments. We find that the industry-level proxies are positively associated with the magnitude of discretionary accruals, volatility of earnings, and the frequency of large earnings increases. Using firm-level data on the firm's actual suppliers and customers, we find that supplier-related variables used to proxy for relationship-specific variables by suppliers are positively related to the magnitude of discretionary accruals. However, we find that the relation between the customer variables and earnings management depends on the size of the firms relative to their customers; we find that the relation is positive only for firms that are larger than their customers.

Examining the consequences of firms' earnings management for suppliers/customers, we find that suppliers and customers invest more in R&D when the level of earnings management by firms is high. This finding suggests that suppliers and customers may not fully undo the extent of accounting discretion exercised by firms. However, earnings management adversely affects the duration of firms' relationships with suppliers and customers. We find that customer-supplier relationships terminate sooner when the magnitude of earnings management is high.

A limitation of our analyses is that we cannot rule out the possibility that the positive relation between the industry-level proxies for relationship-specific investments and the absolute value of discretionary accruals is driven by industry-level omitted variables that are correlated with the magnitude of discretionary accruals. One possible approach to get more insights on this issue is to first identify events where particular relationship-specific investments (e.g., investments tied to a strategic alliance) are undertaken, and then examine the signed discretionary accruals around such events. We leave this issue for future research. Another avenue for future research is to investigate whether relationship-specific investments by customers and suppliers affect the firm's incentive to manipulate real activities (see, e.g., Roychowdhury 2006).

APPENDIX

DATA AND VARIABLES

Construction of the Supplier and Customer Industry-Level R&D Variables

The construction of the supplier and customer industry-level R&D variables requires both the identification of the supplier and customer industries for each firm in our sample and the measurement of the R&D intensity for each of these industries. We rely on the *Use* table of the benchmark input-output (IO) accounts to identify the supplier and customer industries as follows:[32] For each firm in our sample, we first identify its primary SIC code using Compustat's Historical SIC Code data. Since Compustat reports the historical primary SIC code from 1987 onward, we use the 1987 historical SIC code for years prior to 1987. The IO accounts are constructed using the six-digit IO industry classification system. While there is a one-to-one correspondence between the majority of six-digit IO codes and four-digit SIC codes, some IO industries do not correspond to a unique SIC industry. Using the IO-SIC codes conversion table employed by Fan and Lang (2000),[33] we identify the IO codes of our sample firms. We then use the firm's IO code to identify its supplier and customer industries from the *Use* table. We use the 1987, 1992, and 1997 *Use* tables for the periods 1984 to 1989, 1990 to 1994, and 1995 to 2003, respectively. Note that, unlike previous tables, the 1997 benchmark accounts are constructed based on the North American Industry Classification System (NAICS) and not the SIC coding system. Thus, to be consistent across the sample period, we use the 1997 annual updates of the 1992 benchmark tables for the period 1995 to 2003.

---

[32] The Bureau of Economic Analysis at the U.S. Department of Commerce publishes the benchmark input-output (IO) accounts for the U.S. economy every five years. The accounts are based primarily on data collected from economic censuses conducted by the Bureau of Census. The economic censuses provide comprehensive data—including information on industry and commodity production, materials consumed, and operating expenses—that are not available on a more frequent basis. Fan and Lang (2000) and Shahrur (2005) are recent papers that use this data set.

The next step in the construction process is to compute the R&D intensity for each identified supplier and customer industry. To this end, we identify all Compustat firms that operate in each of these industries. We compute the R&D intensity of each industry as the sum of the R&D expenses of all industry firms divided by total industry assets. Following prior studies, we set missing R&D values equal to zero (see, e.g., Bowen et al. 1995). If there are no Compustat firms in a particular six-digit IO industry, then we use firms at the five-digit, four-digit, two-digit, and one-digit levels, respectively. The final step is to compute the weights we assign to each supplier and customer industry, and to make assumptions regarding the R&D intensity of some particular supplier and customer industries. The details of this last step are as follows.

The customer industry-level R&D variable is defined as follows:

$$\mathit{Customer\ Industries\ R\&D} = \sum_{\substack{j=1 \\ j \neq i}}^{n} \mathit{Customer\ Industry\ R\&D}_j * \mathit{Industry\ Percentage\ Sold}_{ji}.$$

In the above equation, *Industry Percentage Sold*$_{ji}$ is equal to industry i's output that is sold to industry j divided by total output of industry i. Total output of industry i is computed by summing the output sold across all customer industries, excluding industry i itself, and including the following final uses: *Personal Consumption Expenditures, Gross Private Fixed Investments*, and *Government Consumption Expenditures and Gross Investment*.[34] Note that if computed using this method, *Industry Percentage Sold*$_{ji}$ will be equal to the output sold to industry j divided by total output of industry i that is consumed domestically, that is, excluding exports.

The results reported in the paper are robust to the inclusion of exports in the above computation. However, if one assumes that exports are sold to industries that have characteristics that are similar to domestic customer industries, then excluding exports from the analysis should be a better choice as we do in the paper. We also make assumptions regarding the R&D intensity of final users. We assign an R&D intensity of zero to the *Personal Consumption Expenditure* customer industry and the mean customer R&D intensity to the *Gross Private Fixed Investment* and to the *Government Consumption Expenditures and Gross Investment* customer industries. To ensure that the results are not sensitive to our assumptions, we repeat our analysis after excluding firms that sell more than 50 percent of their output to final users and find qualitatively similar results.

---

[33] While the construction of the conversion table involves some discretion, it is mostly based on a concordance between the two classification systems provided by the Bureau of Economic Analysis.

[34] *Personal Consumption Expenditures* represent purchases by individual consumers. *Gross Private Fixed Investments* consist of purchases of residential and nonresidential structures and of equipment and software by private businesses. *Government Consumption Expenditures* and *Gross Investment* consist of consumption expenditures and investments by federal, state, and local governments.

The supplier R&D variable is defined as follows:

$$\textit{Supplier Industries R\&D} = \sum_{\substack{j=1 \\ j \neq i}}^{n} \textit{Supplier Industry R\&D}_j * \textit{Industry Input Coefficient}_{ji}$$

where $\textit{Industry Input Coefficient}_{ji}$ is the dollar amount of the jth supplier industry's output used as input to produce one dollar of the output of the ith industry. Industry i's total output is computed by summing the purchases from all supplier industries and adding *Total Value Added*, which includes compensation of employees, indirect business tax and non-tax liability, and other value-added.

Firm-Level Supplier and Customer Data

We collect the firm-level supplier and customer data from Compustat's Segment Tapes for the period 1984–2002. The procedure we follow to identify the customer firms is similar to that used in Fee and Thomas (2004). One challenge in dealing with this data set is that only the customer name is reported, with some of the names abbreviated. In order to get a unique identifier (e.g., CUSIP) for the reported customer, we use an algorithm that compares the order and number of letters in the reported customer names with all company names in the CRSP files for the respective year. We visually inspect the top four matches, and identify the best match. For the vast majority of the customers included in our final sample, we find that the name of the first match is the same as the reported name and none of the other three matches are likely to be the customer. For cases about which we have doubt, that is, when we have more than one possible match, we use information about (1) the industries of the supplier and the possible match and (2) the total sales of the supplier and the possible match along with the dollar sales by the supplier to the customer. Using this information, we identify the match that is more likely to be the customer. In this process, we follow a very conservative approach and include a customer firm only if we are reasonably sure that it is the customer in question.

REFERENCES

Aboody, D., J. Hughes, and J. Liu. 2005. Earnings quality, insider trading, and cost of capital. *Journal of Accounting Research* 43 (December): 651–673.

Alchian, A., and S. Woodward. 1987. Reflections on the theory of the firm. *Journal of Institutional and Theoretical Economics* 143 (March): 110–136.

Allen, J., and G. M. Phillips. 2000. Corporate equity ownership, strategic alliances and product market relationships. *The Journal of Finance* 55 (December): 2791–2815.

Allison, P. D. 1995. *Survival Analysis Using SAS: A Practical Guide*. Cary, NC: SAS Institute Inc.

Armour, H. O., and D. J. Teece. 1980. Vertical integration and technological innovation. *The Review of Economics and Statistics* 62 (August): 470–474.

Arya, A., J. C. Glover, and S. Sunder. 2003. Are unmanaged earnings always better for shareholders? *Accounting Horizons* 17 (Supplement): 111–116.

Baber, W. R., P. M. Fairfield, and J. A. Haggard. 1991. The effect of concern about reported income on discretionary spending decisions: The case of research and development. *The Accounting Review* 66 (October): 818–829.

Baiman, S., and M. V. Rajan. 2002. The role of information and opportunism in the choice of buyer-supplier relationships. *Journal of Accounting Research* 40 (May): 247–278.

Ball, R., and L. Shivakumar. 2006. Role of accruals in asymmetrically timely gain and loss recognition. *Journal of Accounting Research* 44 (May): 207–242.

Barth, M., J. Elliott, and M. Finn. 1999. Market rewards associated with patterns of increasing earnings. *Journal of Accounting Research* 37 (Autumn): 387–413.

Bergstresser, D., and T. Philippon. 2006. CEO incentives and earnings management. *Journal of Financial Economics* 80 (June): 511–529.

Bowen, R., D. Burgstahler, and L. Daley. 1987. The Incremental information content of accrual versus cash flow data. *The Accounting Review* 61 (October): 723–747.

———, L. DuCharme, and D. Shores. 1995. Stakeholders implicit claims and accounting method choice. *Journal of Accounting and Economics* 20 (December): 255–295.

———, S. Rajgopal, and M. Venkatachalam. 2005. Accounting discretion, corporate governance, and firm performance. Working paper, University of Washington, Seattle, WA.

Bradshaw, M. T., S. A. Richardson, and R. G. Sloan. 2001. Do analysts and auditors use information in accruals? *Journal of Accounting Research* 39 (June): 45–74.

Brown, D. T., E. C. Fee, and S. Thomas. 2007. Financial leverage and bargaining power with suppliers: Evidence from LBO transactions. Working paper, University of Florida, Gainesville, FL.

Burgstahler, D., and I. Dichev. 1997. Earnings management to avoid earnings decreases and losses. *Journal of Accounting and Economics* 24 (December): 99–126.

Bushee, B. J. 1998. The influence of institutional investors on myopic R&D investment behavior. *The Accounting Review* 73 (July): 305–333.

Caramanis, C., and C. Lennox. 2008. Audit effort and earnings management. *Journal of Accounting and Economics* 45 (March): 116–138.

Chaney, P., and C. Lewis. 1995. Earnings management and firm valuation under asymmetric information. *Journal of Corporate Finance* 1 (April): 319–345.

Chung, H., and S. Kallapur. 2003. Client importance, nonaudit services, and abnormal accruals. *The Accounting Review* 78 (October): 931–955.

Cohen, D. A., A. Dey, and T. Z. Lys. 2005. Trends in earnings management and informativeness of earnings announcements in the pre- and post-Sarbanes Oxley periods. Working paper, Northwestern University, Chicago, IL.

Coles, J. L., N. D. Daniel, and L. Naveen. 2006. Managerial incentives and risk taking. *Journal of Financial Economics* 79 (February): 431–468.

Cox, D. R. 1972. Regression models and life tables (with discussion). *Journal of the Royal Statistical Society. Series A (General)* B34: 187–220.

Darrough, M., and S. Rangan. 2005. Do insiders manipulate earnings when they sell their shares in an initial public offering? *Journal of Accounting Research* 43 (March): 1–33.

Dechow, P. M., R. G. Sloan, and A. P. Sweeney. 1995. Detecting earnings management. *The Accounting Review* 70 (April): 193–225.

———, and D. J. Skinner. 2000. Earnings management: Reconciling the views of accounting academics, practitioners, and regulators. *Accounting Horizons* 14 (June): 235–250.

———, and I. Dichev. 2002. The quality of accruals and earnings: The role of accrual estimation errors. *The Accounting Review* 77 (Supplement): 35–59.

DeFond, M. L., and J. Jiambalvo. 1994. Debt covenant effects and the manipulation of accruals. *Journal of Accounting and Economics* 17 (January): 145–176.

Demski, J. 1998. Performance measure manipulation. *Contemporary Accounting Research* 15 (Fall): 261–285.

Fan, J. P. H., and L. Lang. 2000. The measurement of relatedness: An application to corporate diversification. *Journal of Business* 73 (October): 629–660.

Fee, E. C., and S. Thomas. 2004. Sources of gains in horizontal takeovers: Evidence from customer, supplier, and rival firms. *Journal of Financial Economics* 74 (December): 423–460.

———, C. J. Hadlock, and S. Thomas. 2006. Corporate equity ownership and the governance of product market relationship. *The Journal of Finance* 61 (June): 1217–1251.

Fitzgerald, K. R. 1996. Proprietary information—Should supplier share it? *Purchasing* (October 3): 55–56.

Francis, J., R. LaFond, P. Olsson, and K. Schipper. 2005. The market pricing of accruals quality. *Journal of Accounting and Economics* 39 (June): 295–327.

Frankel, R. M., M. F. Johnson, and K. K. Nelson. 2002. The relation between auditors' fees for nonaudit services and earnings management. *The Accounting Review* 77 (Supplement): 71–105.

Graham, J. R., C. R. Harvey, and S. Rajgopal. 2005. The economic implications of corporate financial reporting. *Journal of Accounting and Economics* 40 (December): 3–73.

Gu, Z. 2005. Income smoothing and the prediction of future cash flows. Working paper, Carnegie Mellon University. Pittsburgh, PA.

Healy, P. M. 1985. The effect of bonus schemes on accounting decisions. *Journal of Accounting and Economics* 7 (April): 85–107.

———, and J. Wahlen. 1999. A review of the earnings management literature and its implications for standard setting. *Accounting Horizons* 13 (December): 365–383.

Holmstrom, B., and J. Roberts. 1998. The boundaries of the firm revisited. *The Journal of Economic Perspectives* 12 (Fall): 73–94.

Hribar, P., and D. Collins. 2002. Errors in estimating accruals: Implications for empirical research. *Journal of Accounting Research* 40 (March): 105–134.

———, and D. C. Nichols. 2007. The use of unsigned earnings quality measures in tests of earnings management. *Journal of Accounting Research* 45 (December): 1017–1053.

Hunt, A., S. Moyer, and T. Shevlin. 2000. Earnings volatility, earnings management and equity value. Working paper, University of Washington, Seattle, WA.

Jones, J. 1991. Earnings management during import relief investigations. *Journal of Accounting Research* 29 (Autumn): 193–228.

Joskow, P. L. 1987. Contract duration and relationship-specific investments: Empirical evidence from coal markets. *The American Economic Review* 77 (March): 168–185.

Kale, J., and H. Shahrur. 2007. Corporate capital structure and the characteristics of suppliers and customers. *Journal of Financial Economics* 83 (February): 321–365.

Kirschenheiter, M., and N. Melumad. 2002. Can "big bath" and earnings smoothing coexist as equilibrium financial reporting strategies? *Journal of Accounting Research* 40 (June): 761–796.

Klein, B., R. Crawford, and A. Alchian. 1978. Vertical integration, appropriable rents, and the competitive contracting process. *The Journal of Law & Economics* 21 (October): 297–326.

Kothari, S. P., A. J. Leone, and C. E. Wasley. 2005. Performance matched discretionary accrual measures. *Journal of Accounting and Economics* 39 (February): 163–197.

Leuz, C., D. Nanda, and P. D. Wysocki. 2003. Earnings management and investor protection: An international comparison. *Journal of Financial Economics* 69 (September): 505–527.

Levy, D. 1985. The transactions cost approach to vertical integration: An empirical examination. *The Review of Economics and Statistics* 67 (August): 438–445.

Lieberman, M. B. 1991. Determinants of vertical integration: An empirical test. *The Journal of Industrial Economics* 39 (September): 451–466.

Lizzeri, A. 1999. Information revelation and certification intermediaries. *The RAND Journal of Economics* 30 (Summer): 214–231.

Lyons, B. R. 1995. Specific investment, economies of scale, and the make-or-buy decision: A test of transaction cost theory. *Journal of Economic Behavior & Organization* 26 (May): 431–443.

Masten, S. E. 1984. The organization of production: Evidence from the aerospace industry. *The Journal of Law & Economics* 27 (October): 403–417.

McNichols, M. F. 2002. Discussion of the quality of accruals and earnings: The role of accrual estimation errors. *The Accounting Review* 77 (Supplement): 61–69.

Milgrom, P., and J. Roberts. 1992. *Economics, Organization and Management*. Englewood Cliffs, NJ: Prentice Hall.

Rangan, S. 1998. Earnings management and the performance of seasoned equity offerings. *Journal of Financial Economics* 50 (October): 101–122.

Ronen, J., and S. Sadan. 1981. *Smoothing Income Numbers: Objectives, Means, and Implications.* Reading, MA: Addison-Wesley.

Roychowdhury, S. 2006. Earnings management through real activities manipulation. *Journal of Accounting and Economics* 42 (December): 335–370.

Sankar, M. R., and K. R. Subramanyam. 2001. Reporting discretion and private information communication through earnings. *Journal of Accounting Research* 39 (September): 365–386.

Schumacher, U. 1991. Buyer structure and seller performance in U.S. manufacturing industries. *The Review of Economics and Statistics* 73 (May): 277–284.

Shahrur, H. 2005. Industry structure and horizontal takeovers: Analysis of wealth effects on rivals, suppliers, and corporate customers. *Journal of Financial Economics* 76 (April): 61–98.

Shivakumar, L. 2000. Do firms mislead investors by overstating earnings before seasoned equity offerings? *Journal of Accounting and Economics* 29 (June): 339–371.

Simunic, D. A. 1984. Auditing, consulting, and auditor independence. *Journal of Accounting Research* 22 (Autumn): 679–702.

Skinner, D. J., and R. G. Sloan. 2002. Earnings surprises, growth expectations, and stock returns: Don't let an earnings torpedo sink your portfolio. *Review of Accounting Studies* 7 (June): 289–312.

Sloan, R. G. 1996. Do stock prices fully reflect information in accruals and cash flows about future earnings? *The Accounting Review* 71 (July): 289–315.

Snyder, C. M. 1996. A dynamic theory of countervailing power. *The RAND Journal of Economics* 27 (Winter): 747–769.

Subramanyam, K. R. 1996. The pricing of discretionary accruals. *Journal of Accounting and Economics* 22 (August-December): 249–281.

Sweeney, A. P. 1994. Debt covenant violations and managers' accounting responses. *Journal of Accounting and Economics* 17 (May): 281–308.

Teoh, S. H., I. Welch, and T. J. Wong. 1998. Earnings management and the underperformance of seasoned equity offerings. *Journal of Financial Economics* 50 (October): 63–99.

Tirole, J. 1999. Incomplete contracts: Where do we stand? *Econometrica* 67 (July): 741–781.

Titman, S. 1984. The effect of capital structure on a firm's liquidation decision. *Journal of Financial Economics* 13 (March): 137–151.

Trueman, B., and S. Titman. 1988. An explanation for accounting income smoothing. *Journal of Accounting Research* 26 (Supplement): 127–139.

Tucker, J., and P. Zarowin. 2006. Does income smoothing improve earnings informativeness? *The Accounting Review* 81 (January): 251–270.

Ulset, S. 1996. R&D outsourcing and contractual governance: An empirical study of commercial R&D projects. *Journal of Economic Behavior & Organization* 30 (July): 63–82.

Weiss, A. M., and N. Kurland. 1997. Holding distribution channel relationships together: The role of transaction-specific assets and length of prior relationships. *Organization Science* 8 (November): 612–623.

White, H. 1980. A heteroscedasticity-consistent covariance matrix estimator and a direct test for heteroscedasticity. *Econometrica* 48 (May): 817–838.

Williamson, O. E. 1975. *Markets and Hierarchies: Analysis and Antitrust Implications.* New York, NY: Free Press.

———. 1979. Transaction-cost economics: The governance of contractual relations. *The Journal of Law & Economics* 22 (October): 233–261.

———. 1983. Credible commitments: Using hostages to support exchange. *The American Economic Review* 73 (September): 519–540.

THE ACCOUNTING REVIEW
Vol. 83, No. 4
2008
pp. 1083–1099

American Accounting Association
DOI: 10.2308/accr.2008.83.4.1083

The Effect of Honesty and Superior Authority on Budget Proposals

Frederick W. Rankin
Colorado State University

Steven T. Schwartz
State University of New York at Binghamton

Richard A. Young
The Ohio State University

ABSTRACT: Research in budgeting suggests that subordinates may exhibit economically significant degrees of honesty, in spite of pecuniary incentives to do otherwise. This study continues the exploration of honesty in budgeting along two dimensions. First, unlike prior experiments, we measure the incremental effect of honesty by manipulating whether budget requests are made in the form of a factual assertion. Second, prior designs may have emphasized the ethical dimension of budgeting by granting the subordinate wide discretion over setting the budget, whereas we manipulate whether the subordinate or the superior has final authority over setting the budget. We find that less slack is created when budget communication requires a factual assertion in the subordinate authority treatment, but not when the superior has final authority. Hence, we find an incremental effect of honesty only when the subordinate has final authority. We conjecture, and provide some evidence, that this is due to subordinates framing the superior authority situation as one of negotiation where each party acts in his or her self-interest, rather than as an ethical dilemma. This view, that budgeting is essentially devoid of ethical considerations, is consistent with some recent characterizations of budget practices.

Keywords: *participatory budgeting; honesty; slack; experiment.*

Data Availability: *Contact the authors.*

This paper has benefited from helpful discussions with Bryan Church, Carlos Corona, Harry Evans, Jeffrey Hales, Lynn Hannan, Scott Jackson, Murali Jagannathan, Steve Kachelmeier, Dennis Lasser, Volker Laux, Joan Luft, Don Moser, Paul Newman, Kristy Towry, Sean Peffer, Scott Vandervelde, Michael Williamson, and workshop participants at Colorado State University, Emory University, Georgia Institute of Technology, University of South Carolina, Saint Louis University, State University of New York at Binghamton, The University of Texas at Austin, the 2005 Management Accounting Conference, the 2005 Global Management Accounting Symposium, and the 2005 AAA Annual Meeting.

Editor's note: This paper was accepted by Marlys Gascho Lipe.

Submitted: February 2005
Accepted: November 2007
Published Online: July 2008

I. INTRODUCTION

In decentralized firms, the budgeting process is often the manner in which resources are allocated. For this process to be accomplished efficiently, information must be obtained from subordinates who are in close proximity to resource usage. However, if subordinates' objectives diverge from those of the firm, they may withhold or misrepresent their private information. In fact, agency analyses of the budgeting process assume that in the absence of truth-inducing contracts, subordinates will misrepresent their private information to serve their own interests, regardless of the effect on the firm. Such opportunistic behavior by subordinates greatly reduces the value of the budgeting process (Baiman and Evans 1983; Melumad and Reichelstein 1987).

In contrast, many budgeting studies find that individuals do not misrepresent their private information to the extent predicted, in spite of considerable pecuniary incentives to do so (Chow et al. 1988; Waller 1988; Evans et al. 2001; Hannan et al. 2006). These studies suggest that superiors can take advantage of subordinates' tendency to avoid making untrue factual assertions so as to increase the efficiency of the budgeting process. Evans et al. (2001) point out that if subordinates are reluctant to make untrue factual assertions, then contracts that take this behavior into account would result in greater profit than contracts based on the standard agency assumptions.

Prior research uses the construct of *honesty* to explain the tendency of individuals to avoid making untrue factual assertions, despite explicit or implicit incentives to the contrary (Baiman and Lewis 1989; Evans et al. 2001).[1] We maintain this definition of honesty throughout the paper.

There are two reasons why we undertake a further investigation into the effects of honesty on budgeting. First, previous studies such as Evans et al. (2001) and Hannan et al. (2006) have difficulty isolating the effects of honesty because the reporting behavior of the subordinate directly affects the distribution of wealth between the superior and subordinate. Therefore, deviations from self-interested behavior can be attributed either to honesty or to other nonpecuniary motivations such as preferences for the distribution of wealth. Evans et al. (2001) recognizes the importance of the subordinate's concerns for the distribution of wealth between the superior and subordinate and note the need for further research to refine our understanding of the factors that influence the extent of honesty. We address this issue by manipulating the subordinates' mode of budget communication, including one treatment where a factual assertion is required and another treatment where no factual assertion is required. While other-regarding preferences may operate in both cases, only in the former case should honesty be relevant because only in that case is it possible to make an untrue representation. By exploring both forms of communication, we are able to estimate the incremental effect of honesty.

Second, in nearly all studies of honesty in participative budgeting, subordinates have final authority over setting the budget. Because the superior has no ability to deny funding, the subordinate's budget proposal and the form of the contract in place determine the distribution of the profit.[2] It is possible that this approach encourages subjects to frame the budgeting process as an ethical dilemma, triggering honest and/or other non-pecuniary motivations. In contrast, in most organizations budgets are set through a process that includes negotiation between subordinates and superiors (Howell and Sakurai 1992; Anthony and Govindarajan 1994, 383; Fisher, Frederickson, and Peffer 2002). From the subordinate's perspective, this may frame budgeting as a strategic interaction, where each party acts in his or her self-interest, perhaps diminishing an intrinsic motivation to report honestly. In fact, practitioners and academics accuse the budgeting process of being largely devoid of an ethical component (e.g., Jensen 2003; Horngren et al. 2003). For instance, Jensen (2003, 386) provides anecdotal evidence that subordinates view lying and the concealing of information in the budgeting process as a game and, further, notes "that almost no one in this system consciously believes he or she is lying or behaving without integrity." Hence, it is unknown whether honesty would persist in the budgeting process when the superior has final authority over budget approval. We address this issue by administering two levels of budget authority, one where the subordinate has final authority over the budget and one where the superior has final authority over the budget. We further investigate this issue by administering a post-experimental questionnaire, designed to elicit the participants' motivation for their decisions.

---

[1] Our definition is a broad one, including honest behavior due to social conditioning, moral reasoning, and social and environmental cues, among other things. We do not attempt to differentiate among the various motivations for honesty, but doing so in future research may be helpful in furthering our knowledge of budgeting behavior.

[2] In virtually all prior research in participative budging, the experimentalist acts as the superior (Young 1985; Waller 1988; Chow et al. 1988; Chow et al. 1991; Young et al. 1993; Chow et al. 1994; 1995; Evans et al. 2001; Stevens 2002; Fisher et al. 2003). Hannan et al. (2006) utilized subject-superiors, but they played no active role. Fisher et al. (2000), Fisher, Maines, Peffer and Sprinkle (2002) and Rankin et al. (2003) utilized subject-superiors who did play a role in the setting of budgets; however, these studies were designed to examine aspects of budgeting other than honesty.

We find that less slack is created when budget communication requires a factual assertion, but only when the subordinate has final authority over the budget. This finding is consistent with the results of Evans et al. (2001) and Hannan et al. (2006). Because our experimental design facilitates the study of the incremental effect of honesty, our results better demonstrate that honesty may be relevant beyond other nonpecuniary motivations. Standard agency theory maintains the information communicated should not be affected by whether the communication does or does not require a factual assertion. However, our results support the claim made in Evans et al. (2001) that honesty is relevant and that the reporting environment should be designed to take into consideration all aspects of preferences, both pecuniary and nonpecuniary.

In contrast, we do not observe a significant incremental effect of honesty when the superior has final authority. That is, the amount of budgetary slack is similar, regardless of whether budget communication requires the subordinate to make a factual assertion. The apparent reason for this result is that when superiors have final authority, subordinates are motivated primarily by strategic concerns, namely the fear of having their budget proposals rejected. Participant responses to our post-experimental questionnaire confirm that when superiors have final authority, subordinates are concerned with having their budget proposal rejected. Moreover, subordinates' concerns for the welfare of superiors are lower when superiors have authority over the budget. This is consistent with the theory of "crowding out," which suggests that extrinsic control in the form of superior authority will diminish the intrinsic motivation to display honesty in budgeting.

Although superior authority reduces the incremental effect of honesty, budgets contain less slack and superiors' earnings are greater than when subordinates have final authority. This is the case regardless of the mode of budget communication. This result regarding the benefits of formal control is consistent with recent findings. For instance, Evans et al. (2001) find that an optimal hurdle rate contract, in which the project is rejected if the report is above the hurdle, results in greater superior earnings than a trust contract, in which production is guaranteed irrespective of the subordinate's report. Rankin et al. (2003) find that allowing superiors to commit *ex ante* to a hurdle rate results in greater superior earnings than allowing subordinates *ex post* discretion over budget approvals. Finally, in a somewhat different context, Coletti et al. (2005) find that strong controls can enhance trust among individuals and improve performance in collaborative work environments.

The remainder of the paper is organized as follows. Section II describes our setting and predictions. Section III develops our experimental design. Section IV presents the results of the experiment. Section V presents limitations, implications, and conclusions.

II. HYPOTHESIS DEVELOPMENT

Setting

The research design for this study is adapted from a setting used in several studies on budgeting (e.g., Antle and Eppen 1985; Evans et al. 2001; Rankin et al. 2003; Hannan et al. 2006). The implementation of an investment project requires the presence of a subordinate who receives information about the project and a superior whose role is to provide cash. Both the revenue and the probability distribution of the project's cost are known by the subordinate and superior. Subsequently, the subordinate learns the cost of the project and submits a budget to the superior. The superior never learns the actual cost of the project. If the project is implemented, then the subordinate consumes as slack the difference between the funding provided by the superior and the actual cost of the project.[3] The superior receives the residual. If the project is not funded, then both parties receive a zero payout from the project.

Our budgeting task is well suited to the study of honesty. Unlike many previous studies, there is no uncertainty on the part of the subordinate when he submits his budget. Therefore, divergences from standard agency predictions can more clearly be attributed to nonpecuniary motivations, such as honesty, rather than to risk preferences. In addition, the superior never learns the true cost, so impression management is less of an issue.

We manipulate two features of this budgeting setting. First, we manipulate the mode of budget communication. In particular, subordinates' budgets take one of two forms: one that requires a factual assertion and one that does not. In the former case, subordinates report the project's cost and in the latter case, subordinates simply propose a portion of the project's profit to be returned to the superior. That is, in the latter case, the budget takes the form of an offer. Thus, if due to ethical considerations subordinates experience disutility from making explicit misrepresentations of fact, we would expect budgets to contain less slack when reporting requires subordinates to make factual assertions. This manipulation is related to Baiman and Lewis (1989), who allow participants to choose between making an implied assertion about their skill and an otherwise identical contract that contains no implied assertion.

We also manipulate whether the subordinate or superior has final authority over the budget. When the subordinate has final authority, he submits a budget that is automatically accepted. When the superior has final authority, the subordinate submits a budget that the superior either accepts or rejects.[4] While in practice, budget negotiation entails a more complex give-and-take structure, our assignment of final budget authority has the advantage of establishing an unambiguous economic benchmark prediction: The superior will accept any budget that gives her positive earnings and subordinates will therefore propose a budget that results in superiors receiving a minimal amount of earnings.[5]

Hypotheses

Prior research demonstrates that in budget settings similar to ours subordinates trade off pecuniary and nonpecuniary payoffs. Evans et al. (2001) use a measure that they call the percentage of honesty—the percentage of profit available to, but unclaimed by, subordinates. In their study, the amount of profit returned to superiors ranges from 49 percent under a trust contract to 22 percent under a hurdle contract. They take significant measures to maintain subordinate anonymity to ensure the permanence of information asymmetry. Hannan et al. (2006) study face-to-face reporting and manipulate the degree of asymmetric information between subordinates and superiors. Using the same metric as Evans et al. (2001), they find that the proportion of profits returned to superiors ranges from 59 percent to 75 percent.

---

[3] In our setting profit is defined as the difference between revenue and cost for funded projects. Slack is defined as that portion of the profit that the subordinates attempt to capture for themselves via their choices.

[4] A contract that gives the subordinate discretion over the distribution of profit implicitly relies on an assumption of commitment. In particular, the superior commits to accept any budget report. When the superior has final authority, we assume that commitment is either not feasible or that commitment is feasible, but that the superior chooses to retain the right to reject budget reports.

[5] Having superiors either accept or reject projects most readily corresponds to situations involving significant incremental changes in operating budgets or to capital projects, as opposed to core operating budgets.

It is important to note that in both of the above studies the researchers attribute entirely to honesty any deviations from budgets that maximize slack, even though it is possible that other nonpecuniary motivations such as fairness are also relevant. Our budget communication manipulation addresses the question of whether a communication system that requires a factual assertion has incremental value relative to other nonpecuniary motivations.

Another interpretation is our manipulation allows us to explore whether the mode of budget communication affects how subordinates frame the decision task. The theory of decision framing (Cialdini 1996; Tenbrunsel and Messick 1999; Fehr and Gachter 2002) suggests institutional features may serve as environmental cues that determine how individuals mentally frame the budgeting process. When budget communication requires a factual assertion, subordinates might frame the budgeting task as conveying information to the superior. In contrast, when budget communication does not require a factual assertion, it induces the subordinate to frame the budgeting task as merely proposing an allocation of the profit. Therefore, budget communication that requires a factual assertion should make the issue of honesty more relevant. If this framing effect occurs and honesty has an incremental effect, then slack will be lower when budget communication requires a factual assertion. One might then say that honesty can serve as an intrinsic control on budgetary slack.

Whether the superior or subordinate has final authority may also have a framing effect on the subordinate. We base this conjecture on evidence from past budgeting research and simple bargaining situations that have a structure similar to ours. Fisher et al. (2000) explore slack creation when subordinates have final authority and when superiors have final authority. Compared to cases where subordinates have final authority, there is less subordinate effort when superiors impose their final authority over setting budgets, even when controlling for pecuniary incentives.[6] Their results provide evidence that the assignment of final authority to either subordinates or superiors may frame the budgeting task differently. In our setting, subordinate authority may frame the task in a way that highlights subordinates' ethical concerns. That is, when subordinates have final authority over the allocation of the profit, they may view the budgeting task as an ethical dilemma and this could highlight honesty and other nonpecuniary motivations. In consequence, the subordinate may demonstrate more regard for the superior. In contrast, when the superior has final authority, the subordinate must consider the superior's reaction to his budget. That is, it becomes important that the subordinate's allocation of profit *appears* to be fair and reasonable to the superior to avoid rejection, and it may become relatively less important whether the subordinate considers it to *actually* be fair to the superior. Hence, superior authority may induce the subordinate to frame the budgeting task as a strategic interaction devoid of ethical concerns.

---

[6] It is important to specify differences between their setting and ours. They use multiple rounds of negotiation and, in the case of a negotiation impasse, the party with final authority imposes a budget. In our budget setting, superior authority entails the submission of a budget by the subordinate that the superior either accepts or rejects. As mentioned earlier, while this form of superior authority lacks some of the richness of the negotiation found in Fisher et al. (2000), it is consistent with Evans and Moser's (2005) suggestion that it is advantageous for research designs to have a clear economic prediction against which to compare actual behavior.

The main effect of our budget authority manipulation is similar to the differences between ultimatum and dictator games.[7] Specifically, superiors' ability to reject the budget is essentially equivalent to the responder's veto power over proposals in ultimatum games. In contrast, under subordinate authority the subordinate's position resembles that of proposer in a dictator game, wherein all proposals must be accepted. On average, compared to dictator games, proposers offer much more of the available surplus and receivers' earnings are considerably greater in ultimatum games.[8] Hence, findings from these bargaining games suggest that final authority on the part of the superior can serve as an extrinsic control and reduce the amount of slack created by the subordinate.

To summarize, prior research suggests that subordinates' nonpecuniary motivations (intrinsic control) and a superior with final budget authority (extrinsic control) reduce slack. We further conjecture that superior final authority may diminish the role of nonpecuniary motivations. We develop this line of thought somewhat further as we analyze the interaction of our two treatment manipulations.

Our conjectures regarding the interaction of our treatment manipulations are related to the theory of motivational crowding (Frey and Jegen 2001). The theory of motivational crowding specifies a systematic interaction between extrinsic and intrinsic motivation. Specifically, extrinsic controls are thought to devalue intrinsically motivated behavior. For example, extrinsic controls may lead some to believe that they no longer are expected to display intrinsically motivated behavior, or that the superior does not value intrinsically motivated behavior. In our budgeting setting, crowding out suggests that extrinsic controls will diminish the intrinsic motivation to display honesty in budgeting.

The above discussion leads to the following hypotheses. Our first hypothesis maintains that when subordinates have final authority, honesty will have an incremental effect, thus reducing slack. That is, slack will be lower when budget communication requires a factual assertion.

> **H1:** When subordinates have final budget authority, slack will be less when budgeting requires a factual assertion than when it does not require a factual assertion.

Our next hypothesis maintains that when budget communication does not require a factual assertion, superior authority will serve as an extrinsic control, thus reducing slack.

> **H2:** When budgeting does not require a factual assertion, slack will be less when superiors have final authority over budget approval than when subordinates have final authority.

Our first two hypotheses investigate the effects of budget communication and budget authority in isolation. Our interaction argument leads us to predict that when more formal control is introduced, in the form of the superior's ability to reject budget proposals, it will interfere with the subordinate's intrinsic motivation to be honest. Therefore, we predict that budget communication that requires a factual assertion will reduce slack more when subordinates have final authority than when superiors have final authority.

---

[7] An ultimatum game is one in which a proposer offers a split of a surplus to a receiver. If the receiver accepts, then the proposed split is implemented. If the receiver rejects the offer, then both parties receive nothing. A dictator game is identical except the receiver cannot reject the proposal.

[8] The current interpretation of behavior in ultimatum games is that proposers offer something close to what they believe is the minimum amount that the receiver will accept. Further, the rejection and acceptance of offers by receivers is motivated by a simple trade-off between the utility that they get from a monetary payoff that requires accepting a proposer's offer and the utility that they get from rejecting a proposer's offer and, thus, preventing him from receiving a monetary payoff (Camerer 2003).

H3: The decrease in slack associated with budgets requiring a factual assertion will be less when superiors have final authority over budget approval than when subordinates have final authority.

III. EXPERIMENTAL DESIGN

The experimental design employed a 2 × 2 factorial design obtained by crossing two modes of budget communication (Factual Assertion and No Factual Assertion) with two forms of budget authority (Subordinate Authority and Superior Authority). Both factors were manipulated between participants. Participants were undergraduate students from a large university. Each treatment employed 30 participants. Participants were separated by partitions and interacted anonymously through a computer network. Experimental sessions lasted approximately one hour. Participants were remunerated with U.S.$0.01 dollars for every $0.01 experimental dollar earned. The average pay was approximately $19.

Overview

The instrument was adapted from several related studies (Evans et al. 2001; Rankin et al. 2003; Hannan et al. 2006). Participants were assigned the role of superior or subordinate and kept the same role throughout the experiment.[9] The task involved a project that, if funded, yielded revenue of $2.00. The cost of the project (in dollars) followed a uniform distribution with positive support on {0.00, 0.01, 0.02,…,1.99, 2.00}. After learning the cost each subordinate communicated anonymously to the superior. Prior to the funding decision the subordinate learned the cost, but the superior never learned the cost. These facts were explained to all participants in all treatments.

Participants interacted for 20 rounds. After each round, superiors and subordinates were randomly re-matched. This was done to simulate a one-shot setting, while providing participants with substantial experience. Prior to the experimental sessions we randomly generated 15 cost sequences. To facilitate comparisons across treatments, the same 15 cost sequences were used in each experimental treatment. The mean cost across all 20 rounds was 97.85 in each treatment. At the end of each session each participant was remunerated in private with cash. To ensure that we would not know the earnings of any specific individual, a third party placed the cash in an envelope, which participants claimed via unique participant numbers. All aspects of the experiment were common knowledge among all participants with the exception of the actual costs, which were the private information of the subordinates.

Budget Communication Manipulation

In the budget communication manipulation the subordinate either proposed an allocation of the project's profit to the superior (No Factual Assertion treatments), or reported the project's cost to the superior (Factual Assertion treatments). In the No Factual Assertion treatments, after observing the actual cost, the subordinate could allocate any portion of the project's profit between zero and the total profit generated by the project (*$2.00 – actual cost*) to the superior. If the project was implemented, then this allocation determined the payoffs of the subordinate and superior. In the Factual Assertion treatments, subordinates observed the actual cost and then submitted a cost report to the superior. If the project was implemented, then the superior received $2.00 minus the reported cost and the subordinate received the reported cost minus the actual cost. The subordinate was free to report however he or she wished, but the computer program would not allow the report to be less than the actual cost.[10] In addition, in all treatments the subordinate received a $1.00 payment each round, regardless of whether the project was implemented. The $1.00 payment served as a wage and allowed the subordinate to be compensated, even if he returned all of the profits to the superior.[11]

---

[9] In the experiment we used the terms *manager* and *owner*. For consistent exposition we will continue to use the labels subordinate and superior, respectively.

Budget Authority Manipulation

The budget authority manipulation was operationalized as follows. In the Subordinate Authority treatments, which are similar to those used in Evans et al. (2001) and Hannan et al. (2006), the superior's only task was to observe the subordinate's budget communication.[12] In the Superior Authority treatments, the superior has the option to either accept or reject the subordinate's budget. Table 1 summarizes the experimental design ad hypotheses.

IV. RESULTS

We begin with a summary analysis of the experimental data, followed by tests of the hypotheses. We also explore participants' motivations in more detail by analyzing responses to a post-experiment questionnaire and by analyzing the effect of the treatment manipulations on the superiors' earnings.

Summary Analysis

The results for the four treatments are summarized in Table 2 and Figure 1. Table 2 reports summary statistics for all experimental treatments over all 20 rounds. Slack is measured as the amount of slack implied by the subordinate's budget communication regardless of whether the

TABLE 1

Experimental Design

		Budget Authority	
		Superior Authority (SUP-A)	**Subordinate Authority (SUB-A)**
Budget Communication	No Factual Assertion (NFA)	NFA/SUP-A	NFA/SUB-A
	Factual Assertion (FA)	FA/SUP-A	FA/SUB-A

Hypothesis 1: Effect of budget communication with Subordinate Authority.

H1: $Slack(FA, SUB\text{-}A) < Slack(NFA, SUB\text{-}A)$.

Hypothesis 2: Effect of budget approval authority with No Factual Assertion.

H2: $Slack(NFA, SUP\text{-}A) < Slack(NFA, SUB\text{-}A)$.

Hypothesis 3: Effect of interaction between budget approval authority and budget communication.

H3: $Slack(NFA, SUP\text{-}A) - Slack(FA, SUP\text{-}A) < Slack(NFA, SUB\text{-}A) - Slack(FA, SUB\text{-}A)$

---

[10] The restriction that the subordinate could not understate the cost or allocate more than the project's profit prevented the subordinate from receiving a negative payoff from the investment.

[11] Without a wage, the participants would be placed in a position where there would be extreme tension between their payoff and preferences to report honestly. A wage was also used in Evans et al. (2001), Hannan et al. (2006), and Stevens (2002) for the same reason. Note that the wage has no effect on the economic predictions.

[12] In Evans et al. (2001) the superiors were hypothetical. We have subject-superiors in all of our treatments.

TABLE 2

Summary of Mean (Std. Dev.) Results

Treatment	Slack per Round	Subordinate[a] Earnings per Round from Project	Superior Earnings per Round from Project	Superior Rejection Rate
Subordinate Authority/No Factual Assertion	$0.829	$0.829	$0.192	NA
	(0.512)	(0.512)	(0.172)	
Subordinate Authority/ Factual Assertion	$0.643	$0.643	$0.379	NA
	(0.532)	(0.532)	(0.419)	
Superior Authority/ No Factual Assertion	$0.537	$0.474	$0.417	30.7%
	(0.408)	(0.432)	(0.305)	
Superior Authority/ Factual Assertion	$0.516	$0.464	$0.431	30.7%
	(0.388)	(0.420)	(0.326)	

[a] Both subordinate and superior mean per round earnings include all rounds regardless of whether the project was accepted or rejected.

superior accepted the project.[13] The mean maximum potential slack across all 20 rounds was $1.02 for each of our four treatments.[14] Both subordinate and superior mean, per-round earnings include all rounds, regardless of whether the project was accepted or rejected.

Several aspects of the results are immediately apparent. In the Subordinate Authority treatments we find the familiar result that slack is far less than the greatest possible amount. However, in these treatments, slack decreases about 23 percent when budgeting requires the subordinate to make a factual assertion (submit a cost report). In contrast, as illustrated in Figure 1, in the Superior Authority treatments we find little difference in slack across different forms of budget communication. Interestingly, in both Superior Authority treatments the amount of slack is consistent with subordinates focusing on an equal split of the mean maximum possible slack Hence, when the superior has final budget authority, it appears that honesty does not play an important role in the budgeting process.

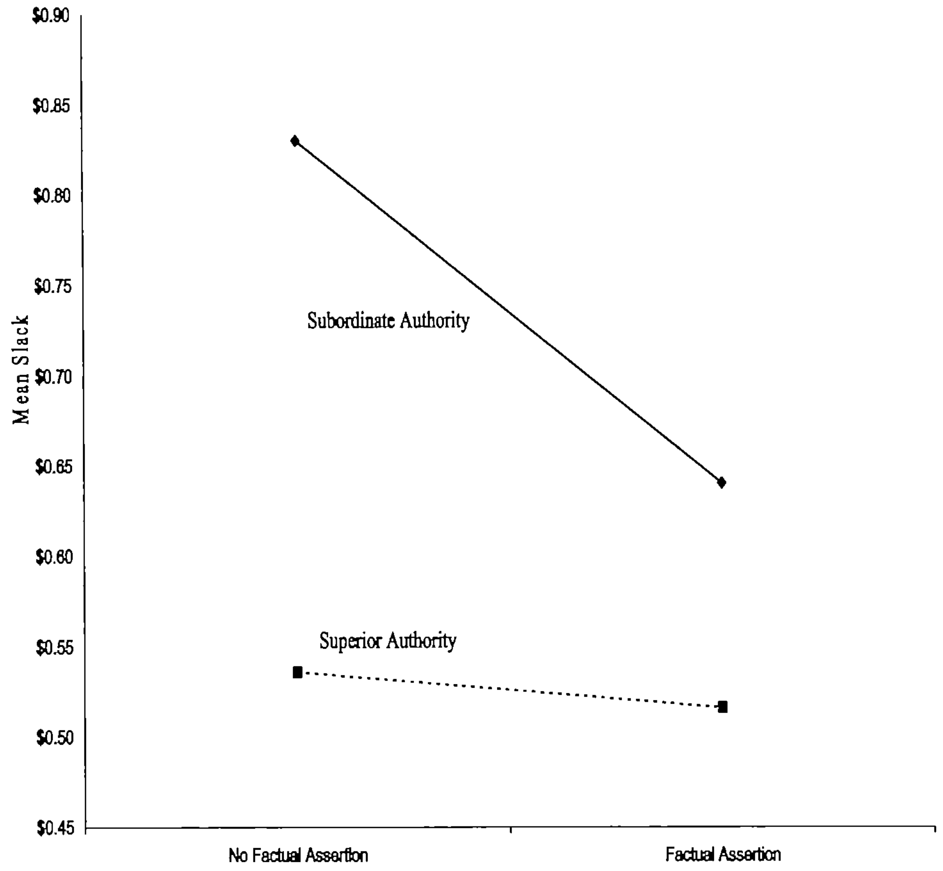
Table 2 also demonstrates that superiors reject a non-negligible fraction of budget proposals even though by doing so they forfeit profit. Also, note that while slack in the Superior Authority treatments is uniformly lower than it is in the Subordinate Authority treatments, there is less of a difference in the earnings of superiors. The smaller difference in earnings reflects the opportunity cost to the superior of rejecting budget proposals, which occurs only in the Superior Authority treatments. We analyze this phenomenon in more detail below.

---

[13] For all statistical tests related to slack, we use the difference between the cost implied by the subordinate's budget communication and the actual cost, regardless of whether the budget was accepted.

[14] Recall, that we used the same 15 cost sequences in each treatment. Hence, each treatment has the same mean actual cost and same mean actual maximum possible slack.

FIGURE 1
Results
Mean Slack



Tests of Hypotheses

For all hypothesis tests, rather than treating multiple responses by the same participant as independent, we calculate mean slack for each subordinate-participant over all rounds, so each subordinate-participant serves as an independent observation.[15] Table 3, Panel A reports statistical tests of H1 and H2 and Panel B reports the test of H3.

Effect of Budget Communication

Our first hypothesis maintains that when the subordinate holds authority over the budget slack will be less when communication requires a factual assertion than when communication does not

---

[15] We also analyzed our data using a repeated-measures ANOVA to check for a period effect. Period was significant, but did not interact with the between-subjects factors. Further, we analyzed mean slack over time, grouping the data by rounds 1–5, 6–10, etc. There is no apparent pattern except for the slight dip in the second interval for all treatments due to the higher cost draws and, hence, lower available slack. Mean available slack in the intervals is 104.78, 92.97, 106.73 and 104.11, respectively.

TABLE 3
Tests of Hypotheses

Panel A: Tests of H1 and H2

Hypothesis 1: Effect of budget communication

	t-statistic	**p-value**
H1: Slack(FA , SUB-A) < Slack(NFA , SUB-A)	1.81	0.0202

Hypothesis 2: Effect of budget approval authority

	t-statistic	**p-value**
H2: Slack(NFA , SUP-A) < Slack(NFA , SUB-A)	5.9	0.0001

Panel B: Tests of H3

Hypothesis 3: Interaction between budget authority and budget communication

H3: Slack(NFA , SUP-A) – Slack(FA , SUP-A) < Slack(NFA , SUB-A) – Slack(FA , SUB-A)

	F-statistic	**p-value**
Authority	14.9	0.0003
Communication	3.62	0.0001
Authority * Communication	2.34	0.1316

FA = Factual Assertion;
NFA = No Factual Assertion;
SUP-A = Superior Authority; and
SUB-A = Subordinate Authority.

require a factual assertion. Support for this hypothesis would provide evidence that honesty serves as an intrinsic control on slack creation. Mean slack in the Subordinate Authority/Factual Assertion treatment is $0.643 and $0.829 in the Subordinate Authority/No Factual Assertion treatment. The null hypothesis of equal mean slack under both forms of budget communication treatments is rejected in favor of less slack in the Subordinate Authority/Factual Assertion treatment ($t = 1.81$, $p = 0.0202$, one-tailed). Hence, when subordinates have final budget authority, honesty has an incremental effect that significantly reduces slack. This finding supports H1. Further, because we employ an experimental design that facilitates the investigation of the incremental effect of honesty, we can more clearly demonstrate the effect of honesty when subordinates have final budget authority. Providing evidence of an effect of honesty in addition to other nonpecuniary motivations is valuable because it has direct implications regarding whether a budgeting system that requires a factual assertion has incremental value to the firm.

Effect of Budget Approval Authority

Our next hypothesis maintains that when budget communication does not require a factual assertion, slack will be less when the superior has final budget authority than when the subordinate has final authority. As seen in Table 2, mean slack in the Subordinate Authority/No Factual Assertion treatment is $0.829, but only $0.537 in the Superior Authority/No Factual Assertion treatment. The null hypothesis of equal mean slack under both treatments is rejected in favor of less slack in the Superior Authority/No Factual Assertion treatment ($t = 5.9$, $p = 0.0001$, one-tailed). This finding supports H2. Hence, when the mode of budget communication is unable to exploit a tendency to exhibit some honesty, because it does not require a factual assertion, formal control in the form of superior authority significantly reduces slack.

It is also important to note that in the Superior Authority/No Factual Assertion treatment, the amount of slack claimed as a percentage of the total surplus falls as actual costs rise. In contrast, we find that in the Subordinate Authority/No Factual Assertion treatment the amount of slack claimed as a percentage of the total surplus stays remarkably consistent across cost levels. This is consistent with subordinates' choice of slack being motivated, in part, by the fear of having their budget proposals rejected.

Effect of Interaction between Budget Approval Authority and Budget Communication

Our final hypothesis maintains that honest behavior will decrease slack less under the Superior Authority treatments than under the Subordinate Authority treatments. Support for this hypothesis would provide evidence that when the superior has final budget authority subordinates' strategic concerns become relatively more important than ethical concerns. In the Subordinate Authority treatments slack decreases 23 percent, from \$0.829 when communication does not require a factual assertion, to \$0.643 when a factual assertion is required. Conversely, in the Superior Authority treatments slack decreases only 4 percent, from \$0.537 when communication does not require a factual assertion, to \$0.516 when a factual assertion is required. Table 3 reports the results of an ANOVA analysis. The results indicate an insignificant interaction between Budget Authority and Budget Communication; however, this is not a directional test. Therefore, the F-statistic is converted to a t-statistic to make directional inferences. The null hypothesis of no difference is rejected in favor of a greater difference in the Subordinate Authority treatments ($t = 1.53$, $p = 0.0658$, one-tailed).[16] This finding supports H3 and is consistent with the idea that formal authority has a crowding effect on the intrinsic motivation to behave honestly. In the next section, we explore the subordinates' various motivations in more detail.

Analysis of Responses to a Post-Experiment Questionnaire

To gain a better understanding of subordinate behavior, we administered a post-experiment questionnaire to explore potential pecuniary and nonpecuniary motivations underlying participants' behavior. Responses range from 1 (strongly disagree) to 7 (strongly agree). Table 4 presents the six questions asked of the participants and the mean responses, by treatment.

First, we pool the data by budget authority. The mean response to the question, "I wanted to treat the owner fairly" is 4.00 in the Subordinate Authority treatments and 3.03 in the Superior Authority treatments. Compared to the Superior Authority treatments, concerns for treating the superior fairly are significantly greater in the Subordinate Authority treatments ($t = 2.46$, $p = 0.0084$, one-tailed). In contrast, the mean response to the question, "I was concerned that the owner desired to be treated fairly" is 2.73 in the Subordinate Authority treatments and 4.4 in the Superior Authority treatments. This concern is significantly greater in the Superior Authority treatments than in the Subordinate Authority treatments ($t = 4.89$, $p = 0.0001$, one-tailed). In the Superior Authority treatments, this question provides some evidence of subordinates' concerns about having their budget proposals rejected. Also, compared to the Subordinate Authority treatments (mean = 3.97), participants in the Superior Authority treatments (mean = 4.53) showed mildly more concern with maximizing their own earnings ($t = 1.47$, $p = 0.0729$, one-tailed).

We also use the post-experiment questionnaire to compare attitudes toward honesty in the Subordinate Authority/Factual Assertion treatment and the Superior Authority/Factual Assertion

---

[16] See McNeil et al. (1996) and Kachelmeier and Towry (2002) with regard to extending the usual logic of a one-sided hypothesis test to directional tests of interactions between two factors.

TABLE 4

Mean (Std. Dev.) Responses to Post-Experiment Questionnaire

	Subordinate Authority/No Factual Assertion	Subordinate Authority/ Factual Assertion	Superior Authority/No Factual Assertion	Superior Authority/ Factual Assertion
I wanted to be honest.	NA	3.60 (1.93)	NA	2.60 (0.88)
I wanted to treat the owner fairly.	4.07 (2.27)	3.93 (1.44)	2.73 (0.77)	3.34 (0.96)
I was concerned that the owner desired to be treated fairly.	2.67 (1.45)	2.80 (0.98)	3.60 (1.02)	5.20 (1.17)
I was concerned that the owner would reject my offer.	NA	NA	4.53 (1.03)	5.67 (0.87)
I wanted to maximize my earnings.	3.93 (1.53)	4.00 (2.07)	4.40 (1.15)	4.67 (0.79)
I wanted to maximize profits.	2.13 (1.15)	3.26 (1.48)	2.53 (0.81)	2.33 (1.08)

Participants responded on a scale of 1 through 7, where 1 = Strongly Disagree,...,7 = Strongly Agree.

treatment. In particular, we compare responses to the question: "I wanted to be honest." The response is significantly greater ($t = 1.77$, $p = 0.0440$, one-tailed) in the Subordinate Authority/ Factual Assertion treatment (mean = 3.6) than in the Superior Authority/Factual Assertion treatment (mean = 2.6). This finding from the Factual Assertion treatments is consistent with our conjecture that honesty concerns are relatively more important when subordinates have final authority over setting the budget. In addition, the results from the question on the desire to treat the owner fairly indicate that equity concerns in general are less important when superiors have final budget authority than when subordinates have final authority.

Analysis of Superiors' Earnings

Though not addressed in the formal hypotheses, of clear interest is the effect of the treatment manipulations on the earnings of the superior. Mean superior earnings are found in Table 2. Pair-wise t-tests for the four treatment combinations yield six comparisons, with each treatment combination contributing 15 independent observations. We find that the Subordinate Authority/No Factual Assertion treatment has significantly lower mean superior earnings than the three other treatments (all p-values <0.05, two-tailed). However, there are no significant differences between the other treatment combinations. One implication of this result is that, compared to the Subordinate Authority/Factual Assertion treatment, either requiring a factual assertion (cost report) or having a superior with authority over budget approval functions equally well in increasing superior earnings.

V. CONCLUSIONS

We find that when the subordinate has final authority over the budget, slack is significantly less when budget communication requires a factual assertion. The significance of this finding is that, while prior studies such as Evans et al. (2001) conclude that honesty plays a role in the budgeting process, it demonstrates an effect from honesty distinct from other nonpecuniary motivations. Therefore, our study suggests it would be beneficial to incorporate honesty into the design of the budgeting process, despite opposite conclusions based on agency theory and the early findings of Baiman and Lewis (1989).

However, we also find that when the superior has final authority, there is no significant difference in the amount of slack created by requiring a factual assertion. Hence, we do not observe an incremental effect from honesty when the superior has final authority. Questionnaire data provide evidence that this results from subordinates framing the situation as negotiation rather than as an ethical dilemma. More precisely, we find that concerns for fairness are greater when the subordinates have final authority. When the superiors have final authority, subordinates demonstrate concern that their proposals will be rejected. This result is consistent with the results from Fisher et al. (2000), who found formal controls such as the superiors imposing their final authority over budget negotiations reduced the subordinate's willingness to put effort into a productive task.

Finally, we find that formal control in the form of superior final authority is beneficial to the firm, in spite of the deleterious effect it has on nonpecuniary preferences. This last result is consistent with results from prior budgeting studies such as Evans et al. (2001) and Rankin et al. (2003). Taken together our three primary findings seem to indicate that the design of budgeting systems requires a delicate balance between promoting nonpecuniary motivations and administering formal controls.

As with all laboratory experiments, the results of this experiment generalize only as far as its design captures important aspects of the setting one wishes to understand. Although along some dimensions we implement a somewhat richer environment than previously administered, we still cannot replicate the cultural aspects that influence behavior within an organization. It is argued that corporate culture can have a profound effect in mitigating undesired behavior. A second limitation involves the manner in which superiors exercise their authority. The authority to reject budget proposals is a simplistic version of the give-and-take that often occurs in budget negotiations. However, a simplified task is desirable in the administration of an experiment because it limits participant confusion, provides greater experimental control, and leads to unambiguous economic predictions. A third limitation is that this paper focuses exclusively on strategic uncertainty, while in practice subordinates may face uncertainly about the future at the time they submit budgets. Hence, even an honest, risk-averse individual may have incentive to build slack into his budget. In other words, such an individual may view his budget as more than just a matter of whether to tell the truth. A fourth possible limitation is that due to the nature of our manipulations, we thought that it was inappropriate to ask honesty-related questions in the No Factual Assertion treatments; in retrospect, it might have been interesting had we done so.

Although our experiment had a more complete mode of strategic interaction than many prior studies, it still provides a rather stark setting in which to study honesty. Further research may focus on richer settings that have such attributes as iterated bargaining, face-to-face communication, and the potential for repeated interactions.

APPENDIX

Instructions for Factual Assertion/Superior Authority Treatment

INTRODUCTION

Welcome and thank you for participating in this experiment. Your pay will depend on the decisions you make during the experiment. At the end of today's session, you will be paid in private and in cash. It is important that you remain silent and do not look at other people's work. If you have any questions, or need assistance of any kind, please raise your hand and an experimenter will come to you.

Before the first decision round begins participants will be assigned as owners or managers. Half of the participants will be assigned as owners and half of the participants will be assigned as managers. You remain as either an owner or manager for all decision rounds. Each of you has an assigned subject number. ***At the beginning of each decision round subjects are randomly paired by subject numbers.*** There will be 20 decision rounds.

OVERVIEW

Each period the cost of implementing a project is randomly determined and revealed only to the manager. The cost is randomly drawn each period from the set of possible costs (0,1,2,...,200). These numbers represent pennies (i.e., 200 = $2.00). Each number is equally likely to be drawn each period. The manager learns the cost. The owner ***never learns the cost.*** If implemented, the project yields revenue of 200.

OWNERS' TASK

For each decision round the owner receives a cost report from the manager. The owner either gives the manager nothing or an amount equal to the manager's reported cost.

MANAGERS' TASK

The manager observes the actual cost. After observing the actual cost, the manager reports a cost to the owner. The reported cost cannot be less than the actual cost. The owner either gives the manager nothing or an amount equal to the manager's reported cost. Since the project yields revenue of 200, the payoff to the owner is 200 minus the amount given to the manager if the project is implemented, and 0 otherwise. The payoff to the manager is the amount received from the owner minus the actual cost if the project is implemented, and 0 otherwise. In addition the manager will receive a payment of 100 each period.

SUMMARY AND SEQUENCE OF EVENTS

The cost is randomly drawn each period from the set of possible costs (0,1,2,...,200). Each number is equally likely to be drawn each period. The manager learns the actual cost and submits a cost report to the owner. The reported cost must be equal to or greater than the actual cost. The owner either gives the manager nothing or an amount equal to the manager's reported cost. At the beginning of each decision round subjects are randomly paired by subject numbers. There will be 20 decision rounds.

Example

If the actual cost is 50, then the total profit is $200 - 50 = 150$. The manager can report any cost between 50 and 200. If the manager reports 133, then the owner either (1) rejects the report and so the manager and owner receive nothing, or (2) accepts the report, gives 133 to the manager, thus the owner earns $200 - 133 = 67$ and the manager earns $100 + (133 - 50) = 183$. That is, if the report is rejected, then the manager and owner receive nothing from the project. If the report is accepted, then the manager receives the fixed payment of 100 plus the difference between the reported cost and actual cost $(133 - 50)$.

REFERENCES

Anthony, R., and V. Govindarajan. 1994. *Management Control Systems*. New York, NY: Irwin.

Antle, R., and G. Eppen. 1985. Capital rationing and organizational slack in capital budgeting. *Management Science* 31: 163–174.

Baiman, S., and J. H. Evans III. 1983. Pre-decision information and participative management control systems. *Journal of Accounting Research* 21 (2): 371–391.

———, and B. Lewis. 1989. An experiment testing the behavioral equivalence of strategically equivalent employment contracts. *Journal of Accounting Research* 27 (Spring): 1–20.

Camerer, C. 2003. *Behavioral Game Theory.* Princeton, NJ: Princeton University Press.

Cialdini, R. 1996. The triple tumor structure of organizational behavior. In *Codes of Conduct, Behavioral Research into Business Ethics*, edited by D. Messick, and A. E. Tenbrunsel. New York, NY: Russell Sage Foundation.

Chow, C. W., J. C. Cooper, and W. S. Waller. 1988. Participative budgeting: Effects of a truth-inducing pay scheme and information asymmetry on slack and performance. *The Accounting Review* 63: 111–122.

———, ———, and K. Haddad. 1991. The effects of pay schemes and ratchets on budgetary slack and performance: A multiperiod experiment. *Accounting, Organizations and Society* 16 (1): 47–60.

———, M. K. Hirst, and M. D. Shields. 1994. Motivating truthful subordinate reporting: An experimental investigation in a two-subordinate context. *Contemporary Accounting Research* 10 (2): 699–720.

———, ———, and ———. 1995. The effects of pay schemes and probabilistic management audits on subordinate misrepresentation of private information: An experimental investigation in a resource allocation context. *Behavioral Research in Accounting* 7: 1–16.

Coletti, A. L., K. L. Sedatole, and K. L. Towry. 2005. The effect of control systems on trust and cooperation in collaborative environments. *The Accounting Review* 80: 477–500.

Evans, J. H., III, R. Hannan, R. Krishnan, and D. Moser. 2001. Honesty in managerial reporting. *The Accounting Review* 76 (October): 537–559.

———, and D. V. Moser. 2005. Agency theory and incentive contracting experiments. Working paper.

Fehr, E., and S. Gachter. 2002. Do incentive contracts undermine voluntary cooperation? Working paper, EU-TMR Research Network.

Fisher, J., J. Frederickson, and S. Peffer. 2000. Budgeting: An experimental investigation of the effects of negotiation. *The Accounting Review* 76 1 (January): 93–114.

———, ———, and ———. 2002. The effect of information asymmetry on negotiated budgets: An empirical investigation. *Accounting, Organizations and Society* 27: 27–43.

———, L. A. Maines, S. A. Peffer, and G. B. Sprinkle. 2002. Using budgets for performance evaluation: Effects of resource allocation and horizontal information asymmetry on budget proposals, budget slack, and performance. *The Accounting Review* 77 (4): 847–865.

———, S. A. Peffer, and G. B. Sprinkle. 2003. Budget-based contracts, budget levels, and group performance. *Journal of Management Accounting Research* 15: 51–74.

Frey, B., and R. Jegen. 2001. Motivational crowding theory. *Journal of Economic Surveys* 15: 589–611.

Hannan, R., F. W. Rankin, and K. L. Towry. 2006. The effect of information systems on honesty in managerial reporting: A behavioral perspective. *Contemporary Accounting Research* 23 (4): 885–919.

Horngren, C. T., G. Foster, and S. M. Datar. 2003. *Cost Accounting: A Managerial Emphasis.* Upper Saddle River, NJ: McGraw-Hill.

Howell, R. A., and M. Sakurai. 1992. Management accounting (and other) lessons from the Japanese. *Management Accounting* (December): 28–34.

Jensen, M. C. 2003. Paying people to lie: The truth about the budgeting process. *European Financial Management* 9: 379–406.

Kachelmeier, S., and K. L. Towry. 2002. Negotiated transfer pricing: Is fairness easier said than done. *The Accounting Review* 77: 571–593.

McNeil, K., I. Newman, and F. J. Kelly. 1996. *Testing Research Hypothesis with the General Linear Model.* Carbondale, Illinois: Southern Illinois Press.

Melumad, N. D., and S. Reichelstein. 1987. Centralization vs. delegation and the value of communication. *Journal of Accounting Research* 25 (Supplement): 1–18.

Rankin, F., S. Schwartz, and R. Young. 2003. Management control using non-binding budgetary announcements. *Journal of Management Accounting Research* 15: 75–93.

Stevens, D. 2002. The effects of reputation and ethics on budgetary slack. *Journal Management Accounting Research* 14: 153–171.

Tenbrunsel, A. T., and D. M. Messick. 1999. Sanctioning systems, decision frames, and cooperation. *Administrative Science Quarterly* 44: 684–707.

Waller, W. S. 1988. Slack in participative budgeting: The joint effects of a truth-inducing pay scheme and risk preferences. *Accounting, Organizations and Society* 13: 87–98.

Young, S. M. 1985. Participative budgeting: The effects of risk aversion and symmetric information on budgeting slack. *Journal of Accounting Research* 23: 829–842.

———, J. G. Fisher, and T. M. Lindquist. 1993. The effects of intergroup competition and intragroup cooperation on slack and output in a manufacturing setting. *The Accounting Review* 68: 466–481.

THE ACCOUNTING REVIEW
Vol. 83, No. 4
2008
pp. 1101–1124

American Accounting Association
DOI: 10.2308/accr.2008.83.4.1101

Extracting Forward-Looking Information from Security Prices: A New Approach

Dan Weiss
Tel Aviv University

Prasad A. Naik
University of California, Davis

Chih-Ling Tsai
University of California, Davis

ABSTRACT: This paper proposes a new index to extract forward-looking information from security prices and infer market participants' expectations of future earnings. The index, called market-adapted earnings (MAE), utilizes stock returns and fundamental accounting signals to estimate market expectations of future earnings at the firm level. MAE outperforms time-series models (e.g., random-walk) in predicting future earnings. Results demonstrate the usefulness of MAE for firms that have no analyst following.

Keywords: *single-index-model; market-adapted earnings.*

I. INTRODUCTION

The prices-lead-earnings stream of research suggests that security prices reflect a richer information set than historical earnings because prices reflect all information available to market participants (Beaver et al. 1980, hereafter BLM). Several studies examine the information content of security prices with respect to future earnings (e.g., BLM; Collins et al. 1987; Ayers and Freeman 2000). However, as Kothari (2001, 148) argues, "researchers have found it difficult to harness the information in prices at the firm level to make an economically important improvement." This challenge motivates us to develop an improved proxy for the market expectations of future earnings.

To construct an improved proxy, we employ a new method to extract information from security prices at the firm level. Similarly to BLM, we utilize information in security prices to infer expected future earnings. However, our model differs from BLM in two ways: we allow for (1) a nonlinear returns-earnings relationship and (2) multiple accounting signals. Because of the

---

The authors are grateful for valuable discussions with and constructive suggestions from Gil Aharoni, Joseph Aharony, Yakov Amihud, Eli Amir, Brad Barber, Uri BenZion, Amihud Dotan, Haim Falk, Dan Givoly, Paul Griffin, Itay Kama, Lakshmanan Shivakumar, and Avi Wohl. The authors thank the editor, Patricia Dechow, and two anonymous referees for their insightful comments that enriched the paper. Comments from the participants of the Tel Aviv Conference in Accounting are highly appreciated. The authors thank Michael Bowers for outstanding research assistance.

Editor's note: This paper was accepted by Patricia N. Dechow.

Submitted: February 2006
Accepted: December 2007
Published Online: July 2008

nonlinearity and the multivariate setting, neither BLM's grouping technique nor reverse regression (e.g., Beaver et al. 1987) can be used. As a result, we apply the recently developed Single-Index Model (SIM), which is a semiparametric model (see, e.g., Horowitz 1998) that provides an approach for efficient estimation in a multi-dimensional environment without assuming a linear returns-earnings relationship.

Using SIM, we construct an index, called *market-adapted earnings* (MAE), which incorporates information from stock returns together with multiple accounting signals to estimate market expectations of future earnings change. Unlike the equal-weight index proposed by Lev and Thiagarajan (1993, 210), MAE places unequal market-based weights on fundamental accounting signals. Hence, we expect MAE to provide better predictions, especially because it also incorporates information from both stock returns and fundamental accounting signals through a nonlinear link function. To this end, we use MAE to forecast one-year-ahead earnings change and examine whether it improves the prediction of future earnings.

Based on a sample of 636 firms from 1992–2001, we find that MAE results in more accurate earnings forecasts than either the random-walk model or an accounting-based model (Abarbanell and Bushee 1997; Lev and Thiagarajan 1993). Specifically, the median absolute forecast error of MAE is 20.9 percent (17.0 percent) lower than the median absolute forecast error of the random-walk (accounting-based) model. In addition, the prediction accuracy of MAE over the time-series models increases as the information environment becomes richer (i.e., the number of analysts covering a firm increases).

How do MAE predictions compare to analysts' forecasts? We find that the median absolute forecast error of analysts' forecasts is 21.0 percent lower than that of MAE, which is expected because analysts utilize a larger information set than MAE (e.g., Fried and Givoly 1982; O'Brien 1988). Furthermore, the analysts' advantage over MAE increases when more information is available. However, financial analysts do not supply one-year-ahead earnings forecasts for all firms; only less than half of the Compustat universe is covered by the Institutional Brokers' Estimate System (I/B/E/S).

For firms with no analyst coverage, the median absolute forecast error for MAE is 14.4 percent (12.0 percent) lower than that for random-walk (accounting-based) model. Furthermore, MAE predicts 55.2 percent (53.6 percent) observations more accurately than the random-walk (accounting-based) model. Thus, MAE outperforms both the random-walk and accounting-based models. The above findings demonstrate the usefulness of MAE for an accurate earnings prediction when no analyst following is available.

In sum, this study contributes to the literature in three ways. First, we show that researchers can benefit from improved estimation of market expectations of future earnings for the sizable class of firms without analyst coverage by extracting forward-looking information from stock prices. Second, we introduce the SIM methodology that is shown to be a useful tool for extracting information from security prices. Third, we demonstrate that the accuracy of earnings prediction increases as the information set is more comprehensive.

The paper continues as follows. Section II reviews the relevant literature. Section III presents our research design, describes the SIM methodology, and displays results from SIM estimations. Section IV compares the prediction accuracy of market-adapted earnings with analysts' forecast as well as both the random-walk and accounting-based models. Section V demonstrates the benefit of MAE for firms without analyst coverage. Section VI concludes.

II. LITERATURE REVIEW

Prices-Lead-Earnings

The concept of prices leading earnings was introduced by BLM, which is based on the premise that security prices reflect a richer information set than do the time-series of earnings.[1] Insofar as current price is the capitalized present value of a firm's expected future earnings, security prices contain useful information for the prediction of future earnings growth. BLM assume that earnings follow a compound stochastic process, and they infer market participants' expectations regarding future earnings from observed changes in security prices. They assess the distribution of future earnings conditionally on known prices and earnings, and they expand the information set underlying inferred earnings expectations from known earnings to known prices and earnings. Furthermore, BLM provide evidence that price-based forecasts are slightly more accurate than the random-walk model with a drift.[2]

BLM use a grouping method, which diversifies away the measurement error in earnings. Because grouping entails loss of estimation efficiency, Beaver et al. (1987) introduce a reverse regression to exploit information contained in prices. Notably, the reverse regression places the measurement error in the disturbance term, rather than in the explanatory variable.[3] Using another approach involving simultaneous equations, Beaver et al. (1997) provide evidence that earnings and prices are endogenously determined.

To examine the availability of rich information as a driver for prices leading earnings, Freeman (1987) shows that the security prices of large firms anticipate accounting earnings earlier than those of small firms. In the same line, Collins et al. (1987) use firm size as a proxy for the richness of the information environment and examine its relationship to the predictive power of price-based earnings forecasts. They find that price-based earnings forecasts reduce forecast error when compared with time-series models for large firms, but increase forecast error for small firms. Later, Ayers and Freeman (2000, 2003) indicate that large firms' prices also have a longer lead than small firms' prices with respect to industry-wide earnings, and they provide evidence that price leads increase as analysts' coverage and institutional ownership increase.[4] Moreover, Kothari and Sloan (1992) provide evidence that price-based earnings forecasts are informative in long-horizon settings.

Table 1 summarizes pertinent dimensions of the above studies. In sum, this line of research indicates that using the prices-lead-earnings framework results in a marginal predictive advantage over random-walk (with or without drift) for predicting one-year-ahead earnings, which raises questions regarding our ability to exploit information incorporated in prices. To address this problem, we propose a new methodology for utilizing information incorporated in security prices and focus on retrieving forward-looking information with respect to one-year-ahead earnings.

Fundamental Analysis

The second line of research linked to this study is the fundamental analysis literature, which uses financial ratios as leading indicators of future performance. This line of research exploits

---

[1] See Brown (1993) for a literature review on time-series models for earnings forecasting.

[2] BLM report that the mean absolute error of price-based forecasts is 1.8 percent lower than the mean absolute error of a random-walk with drift forecasting model (see BLM, Table 4).

[3] An immediate benefit of reverse regression is an unbiased slope coefficient. Cready et al. (2000) further analyze the biases in estimated coefficients when reverse regression is used in a multi-interacted variable setting. See also Kothari (1992).

[4] Ayers and Freeman (2003) and Jiambalvo et al. (2002) report that institutional ownership enhances prices leading earnings. Institutional ownership is characterized as professional and sophisticated, but does not necessarily imply a rich information environment.

TABLE 1

Comparative Summary of Literature Review

	Prices-Lead-Earnings			**Fundamental Analysis**			
Paper	Beaver et al. (1980)	Beaver et al. (1987)	Collins et al. (1987)	Ou and Penman (1989b)	Lev and Thiagarajan (1993)	Abarbanell and Bushee (1997)	This paper
Goal	"We infer market participants' expectations regarding future earnings from observed changes in security prices"	Suggest reverse regression "to assess the information content of security prices with respect to accounting earnings."	"focusing on firm size and its relation to the predictive accuracy of price-based earnings forecasts."	Compare the ability of security prices and accounting signals to predict future earnings.	"identify...a set of financial variables (fundamentals) claimed by analysts to be useful in security valuation."	"We investigate how detailed financial statement data ...enter the decisions of market participants by examining whether... signals are informative about subsequent earnings changes."	We examine whether information incorporated in stock returns and accounting signals, when taken together, can improve the prediction of future earnings (over existing models and analysts' earnings forecasts).
Measure used for earnings prediction[a]	$Exp[E_{t+j} \mid E_t, P_t]$	$Exp[E_{t+j} \mid P_t]$	$Exp[E_{t+j} \mid P_t]$	$Exp[Sign\ E_{t+j} \mid A_t]$, $Exp[E_{t+j} \mid E_t, P_t]$	$Exp[Sign\ E_{t+j} \mid A_t]$	$Exp[E_{t+j} \mid A_t]$ and $Exp[SignE_{t+j} \mid A_t]$	$Exp[MAE_t \mid P_t, A_t]$

(continued on next page)

TABLE 1 (continued)

	Prices-Lead-Earnings			Fundamental Analysis			
Method	OLS + Grouping data	Reverse Regression	Reverse Regression	Logit model used to generate an index (called Pr)	Score based on good or bad news in accounting signals	OLS	Single-index model (Semiparametric)
Model	Linear	Linear	Linear	Linear	Linear	Linear	Nonlinear
Independent signals	Earnings only	Security prices	Security prices	18 fundamental signals	Earnings and 12 fundamental signals	Earnings and nine fundamental signals	Stock returns, earnings, and four fundamental signals
Earnings prediction	"This approach can potentially lead to earnings forecasting models that are more accurate than the random-walk with a drift."	"Provides the basis for forecasting earnings based upon current and past values of price changes."	"Price-based earnings will outperform univariate time-series forecasts by a greater margin for larger firms."	Information in prices that leads future earnings is contained in financial statements.	"relating the fundamental-based quality scores to subsequent earnings changes."	"We find that fundamental signals have incremental explanatory power relative to current-year earnings."	SIM outperforms random-walk and accounting-based models in accurately predicting earnings for firms with no analyst coverage.

---

[a] P = security prices; E = reported earnings; A = accounting signals reported in financial statements.

accounting information reported in financial statements to predict future earnings and identify mispriced securities. Ou and Penman (1989a) combine a large set of accounting signals into an index that expresses the probability of a one-year-ahead earnings increase based on the signals. Ou (1990) employs this index to provide evidence that investors use non-earnings accounting variables to revise their expectations of future earnings. Ou and Penman (1989b) also compare the ability of security prices and accounting signals to predict future earnings, arguing that information in prices that leads future earnings is contained in financial statements. In this study, we examine a related aspect of Ou and Penman's claim using a new methodology that utilizes information used by market participants in forming their expectations on future earnings.

In addition to the above studies, Lev and Thiagarajan (1993) report evidence on the value-relevance of 12 accounting signals and demonstrate that an equally weighted index of the ratios is informative in assessing earnings persistence and change. Later, Abarbanell and Bushee (1997, 5) use accounting signals suggested by Lev and Thiagarajan (1993) in a linear earnings forecasting model and show an incremental improvement in explanatory power over the current-year reported earnings change.

Although the fundamental analysis literature (see Table 1) generally supports the ability of fundamental ratios to forecast future earnings, the lure of above-normal returns based on fundamental analysis demonstrates that the information contained in these signals is not fully incorporated into prices (e.g., Ou and Penman 1989a; Abarbanell and Bushee 1998; Rajgopal et al. 2003). Hence, several studies employ ratios that combine information from both security prices and earnings; for instance, Penman (1998), and Fama and French (2000) use price-earnings or price-to-book ratios to predict earnings. In this paper, we examine whether the information incorporated in stock returns and accounting signals, when taken together, can improve the prediction of future earnings.

III. RESEARCH DESIGN

This study utilizes information incorporated in stock returns and accounting signals for estimating earnings components that are expected to persist. The logic of our model stems from BLM (1980, 4), who characterize future earnings as resulting from a combination of two processes:

(1) Value-relevant earnings: a process reflecting the impact on earnings of events that affect security prices, i.e., have a valuation implication.
(2) Noise in earnings: a process capturing value-irrelevant events resulting in an earnings component with no effect on security prices, i.e., uncorrelated with stock prices or returns. This process includes earnings components that are not expected to persist.

To show that reported earnings do not follow a random-walk process, BLM use the information incorporated in security prices. They introduce a first-order moving average of the first differences in earnings and predict a linear relationship between the percentage change in price and the percentage change in earnings. Our basic motivation is similar to BLM (1980, 23): "viewing earnings as a compound process ... provides a basis for forecasting earnings." However, our prediction model differs from BLM since we not only relax the linearity assumption and allow for a nonlinear returns-earnings relationship, but also incorporate multiple accounting signals.

In the context of nonlinearity, Freeman and Tse (1992), Cheng et al. (1992), Das and Lev (1994), and Beneish and Harvey (1998) report on the S-shaped returns-earnings relationship. The economic rationale underlying the S-shape is that the market does not expect extreme earnings changes to be permanent, and the S-shape is interpreted as reflecting small abnormal returns to extreme earnings changes. Das and Lev (1994) adopt a nonparametric estimation procedure, locally weighted regression, to demonstrate the superior prediction power of out-of-sample stock returns over a linear specification. Following earlier research, they suggest differential earnings persistence as a source of nonlinearity.

In the context of multiple accounting signals, Lev and Thiagarajan (1993) report significant associations of multiple fundamental signals with (1) stock returns, and (2) the expected direction of future earnings change. Keeping prediction in mind, these associations may impede a linear regression of future earnings changes on a set of current fundamental accounting variables and stock returns due to multicollinearity.

In sum, Das and Lev (1994) use earnings as the only explanatory variable (at the exclusion of supplementary signals[5]) in a nonparametric model to study nonlinearity, whereas the fundamental analysis studies formulate linear parametric models to incorporate multiple signals (at the exclusion of nonlinearity). To combine both the nonlinearity and multiple signals in a common framework, we propose semiparametric SIM to predict future earnings.

Single-Index Model (SIM)

SIM is a semiparametric model for estimating a conditional mean function in a multi-signal setting.[6] Let R_{it} be stock return of firm i at year t, and let S_{it} be a $1 \times k$ random vector of realized accounting signals ($k = 5$, reported earnings change and four supplementary fundamental accounting signals). In SIM, the conditional mean function is $E[R_{it} \mid S_{it}] = G(S_{it}\beta_t)$, where β_t is an unknown $k \times 1$ constant vector, $\beta_t = (\beta_{0t}, \beta_{1t}, \beta_{2t}, \beta_{3t}, \beta_{4t})'$ in our case, and $G(.)$ is an unknown link function, whose specific functional form is determined by the data, rather than being assumed by researchers. For the sake of identification, we let $\beta_{0t} = 1$ (see Horowitz 1998, 15), which does not affect the prediction (more on this issue in the following subsection). In addition, $G(.)$ is assumed to be a differentiable function on the support of $S\beta$, where the scalar index $S\beta$ is the market-adapted earnings, MAE. Thus the single-index model is given by the cross-sectional regression model:

$$R_{it} = G_t(MAE_{it}) + \varepsilon_{it}, \tag{1a}$$

where MAE_{it} is given by:

$$MAE_{it} = \Delta E_{it} + \Sigma_j S_{jit}\beta_{jt}, \quad j = 1,\ldots,4. \tag{1b}$$

Using stock returns, earnings change and four supplementary accounting signals, we estimate MAE_{it} to obtain the relative weights β_{jt}. Consequently, the estimated MAE_{it} combines the earnings change and the four supplementary accounting signals with their corresponding estimated $\hat{\beta}_{jt}$ as follows:

$$M\hat{A}E_{it} = \Delta E_{it} + \sum_{j=1}^{4} S_{jit}\hat{\beta}_{jt}. \tag{2}$$

The form of MAE_{it} is similar to Abarbanell and Bushee's (1997, 5) earnings forecast model in its linear structure. Linear indexes for earnings predictions have been widely employed in the fundamental analysis literature (e.g., Lev and Thiagarajan 1993; Penman 1998). The function $G(.)$, as well as the vector β, are estimated endogenously by using information on both stock returns and fundamental accounting signals. In other words, the information content of stock returns is used to estimate the link function $G(.)$ and the market-based β-coefficients.

---

[5] Das and Lev (1994, 361) use a random sample of 622 observations for a nonparametric investigation of nonlinearity in the returns-earnings relation because "it is very computer intensive to estimate a total of 6,220 firm-year observations pooled across all ten years."

[6] See Horowitz (1998) for an in-depth discussion of single-index models. Except for Ait-Sahalia and Brandt (2001), who applied it in the finance literature, we believe this study marks the first application of SIM in the accounting literature.

We achieve an efficient estimation of the index MAE_{it} *without* assuming a linear (or even pre-specifying a nonlinear) relationship between earnings and stock returns. The estimated $\hat{\beta}_{jt}$ are obtained from Li's (1991) Sliced Inverse Regression method as described in Naik and Tsai (2001). It enables us to extract linear combinations of explanatory variables without a pre-specified parametric model. The Appendix presents a detailed description of the estimation procedure.

SIM retains the desirable features of linear models, such as simplicity and interpretability of results, yet incorporates nonlinearity via the link function $G(.)$. Furthermore, SIM possesses the following four advantages:

(1) SIM uses information in stock returns to set the relative weights among the multiple signals. Lev and Thiagarajan (1993, 210) mention that the rather coarse nature of their index is due to the equal weights of the fundamental accounting signals, and Abarbanell and Bushee (1997, 8) argue that equally weighting all the signals may induce inaccuracy. The market-based β-coefficients estimate the relative weights of the fundamental signals as perceived by market participants.

(2) SIM allows us to test the hypothesis that the information in fundamental accounting signals is irrelevant with respect to market expectations of future earnings: H: $\beta_{1t} = \cdots = \beta_{4t} = 0$. If some of the fundamental signals are irrelevant with respect to market expectations of future earnings, then there will be no significant difference between the specifications with or without these signals.

(3) SIM extends Lev and Thiagarajan's (1993) model to a nonlinear setting. The nonlinear function $G(.)$ allows for asymmetric reactions to differential changes.[7]

(4) SIM avoids the curse of dimensionality because the index combines the variables in S. Therefore, SIM allows for the estimation of $G(.)$ with the same degree of precision that it would have if a one-dimensional index were observed (Horowitz 1998, 6). As a result, SIM uses a reasonable sample size to achieve efficient computations.

Market-Adapted Earnings to Forecast Future Earnings

To estimate market expectations of future earnings, we construct $M\hat{A}E^*_{it}$, which transforms $M\hat{A}E_{it}$ in Equation (2) as follows:

$$\begin{aligned} M\hat{A}E^*_{it} &= M\hat{A}E_{it} \times \frac{\overline{\Delta E_{it}}}{\overline{M\hat{A}E_{it}}} \\ &= \left(\frac{M\hat{A}E_{it}}{\overline{M\hat{A}E_{it}}}\right) \times \overline{\Delta E_{it}}, \end{aligned} \tag{3}$$

where $\overline{\Delta E_{it}}$ and $\overline{M\hat{A}E_{it}}$ are the mean current earnings change and the mean $M\hat{A}E_{it}$, respectively. This transformation ensures that the mean value of the scaled $M\hat{A}E^*_{it}$ equals the mean value of reported earnings changes, $\overline{\Delta E_{it}}$. In other words, the sum of noise components in ΔE_{it} across all firms is zero.

---

[7] When the true link function is linear, i.e., $G(S\beta) = S\beta$, then changes in S generate proportional changes in stock returns.

This transformation achieves two goals. First, the ratio in the parenthesis of Equation (3) is unit-free (i.e., dimensionless). Consequently, we can set any nonzero value for the coefficient of ΔE_{it} in Equation (2) (i.e., β_{0t} other than 1) and obtain the same values for the scaled $M\hat{A}E^{*}_{it}$. Hence the assumption $\beta_{0t} = 1$ does not affect $M\hat{A}E^{*}_{it}$. Second, to forecast future earnings change, we multiply that ratio by $\overline{\Delta E_{it}}$. Note that both $M\hat{A}E^{*}_{it}$ and $M\hat{A}E_{it}$ contain information not only from accounting signals, but also from stock returns. Thus, the prediction procedure is well identified. We will employ $M\hat{A}E^{*}_{it}$ as our proxy for predicting future earnings change $\Delta E_{i,t+1}$.

Another property of $M\hat{A}E^{*}_{it}$ is that it is equivalent to a random-walk when the link function $G(.)$ is linear with no supplementary accounting signals, i.e., Equation (1a) becomes $R_{it} = \alpha_t + \beta_{0t}\Delta E_{it} + \varepsilon_{it}$. To see this point, we express Equation (3) as follows:

$$
\begin{aligned}
M\hat{A}E^{*}_{it} &= M\hat{A}E_{it} \times \frac{\overline{\Delta E_{it}}}{\overline{M\hat{A}E_{it}}} \\
&= (\hat{\beta}^{SIM}_{0t}\Delta E_{it}) \times \frac{\overline{\Delta E_{it}}}{\hat{\beta}^{SIM}_{0t}\overline{\Delta E_{it}}} \\
&= \Delta E_{it}
\end{aligned}
$$

Hence, the resulting $M\hat{A}E^{*}_{it}$ in this case is reduced to ΔE_{it}.

To gain insight into the potential advantage of our proposed earnings prediction model, we compare incremental predictive accuracy of the proposed model with the three benchmarks: (1) the classical random-walk; (2) the earnings forecast model of Abarbanell and Bushee (1997), which is based on Lev and Thiagarajan's (1993) fundamental accounting signals and reports significant relationships between most accounting signals and future earnings change; (3) the analysts' earnings forecasts for firms with analyst following.

Data

In the context of fundamental information analysis, Lev and Thiagarajan (1993) select 12 accounting signals of which five (gross margin, inventory, sales and administrative expenses, accounts receivable, and capital expenditures) are significant at the 5 percent confidence level (see their Table 2). Our preliminary analysis shows that gross margin, inventory, sales, and administrative expenses are significant, accounts receivable is marginally significant, and capital expenditures is insignificant. As a result, we chose the first four signals, which focus on the four key firm activities: profitability of sales, logistic operations, marketing and administration, and management of clientele. An advantage of excluding insignificant variables is that it enhances the precision of estimated parameters (Greene 2003, 151).

To measure the four accounting signals, we follow Lev and Thiagarajan (1993), who attach "good" or "bad" signs to accounting indicators of future economic performance based on analysts' interpretations, such that larger values indicate bad news. For instance, we compute the annual percentage change in inventory minus the percentage change in sales for each firm-year in the sample. Table 2 presents the definitions for the four signals.[8]

In addition to the above accounting signals, we use earnings per share before extraordinary items and discontinued operations (Compustat #58), as a measure of the reported earnings, E_t, deflated by share price at the beginning of the fiscal year. Changes in reported earnings, ΔE_t, are

---

[8] Additional discussion and references are in Lev and Thiagarajan (1993, 192).

TABLE 2

Definitions of Four Supplementary Accounting Variables

Accounting	Variables	Measurement	Good News	Bad News
ΔINV	Change in inventory[a]	Δinventory (#78 or #3) − Δsales (#12)	<0	>0
ΔGM	Change in gross margin	Δsales (#12) − Δgross margin (#12-#41)	<0	>0
ΔSGA	Change in sales and administrative expenses	Δsales and administrative expenses (#189) − Δsales (#12)	<0	>0
ΔREC	Change in accounts receivable	Δaccounts receivable (#2) − Δsales (#12)	<0	>0

[a] The inventory variable used is finished goods (when available) or total inventories (otherwise).

Following Lev and Thiagarajan (1993) and Abarbanell and Bushee (1997), the variables are defined such that good (bad) news is based on its negative (positive) expected relation with future benefits. Annual percentage changes are computed for each variable. Compustat items are in parentheses.

measured by the annual change in reported earnings deflated by share price at the beginning of fiscal year.[9] We also note that good news in each of the supplementary non-earnings signals is expressed by negative values and so the coefficients $\beta_{1t},\ldots,\beta_{4t}$ are expected to have negative values.

To measure the stock returns, we obtain information from Compustat annual files and the Center for Research in Security Prices (CRSP) monthly files. Annual abnormal return, R_{it}, is measured by the accumulated raw stock returns over the 12 months (from three months after the fiscal year begins until three months after the fiscal year-ends) minus the CRSP equally weighted monthly returns accumulated for the same period (see Das and Lev 1994).

To allow for intertemporal analysis, we follow Das and Lev's (1994, 360) approach to construct a constant-firm sample. As a result, the sample consists of firms that have complete data on Compustat and CRSP files for returns, earnings and the four accounting signals described in Table 2 for the 11-year period from 1990 to 2000, resulting in 636 firms.[10] The variables are adjusted for splits and dividends; high and low 1 percent of the variables are winsorized.

Estimating SIM

We estimate the following cross-sectional SIM model:

$$R_{it} = G(MAE_{it}) + \varepsilon_{it},$$

where $MAE_{it} = \Delta E_{it} + \beta_{1t}\Delta INV_{it} + \beta_{2t}\Delta GM_{it} + \beta_{3t}\Delta SGA_{it} + \beta_{4t}\Delta REC_{it}$.

Table 3 presents the estimates of the regression coefficients and t-statistics. The average estimated effects across years for changes in inventory valuation, changes in gross margins, changes in SG&A, and changes in accounts receivable are −0.361 (−2.30), −1.062 (−3.20),

---

[9] Kothari (1992) demonstrates that the error-in-variables problem in a price-earnings regression is mitigated when earnings are deflated by share price and prices are assumed to lead earnings.

[10] This restriction may introduce a survivorship bias in our analysis (see also Das and Lev 1994).

TABLE 3

Single-Index Model Estimates of Regression Coefficients

SIM: $R_{it} = G(MAE_{it}) + \varepsilon_{it}$,
where $MAE_{it} = \Delta E_{it} + \beta_{1t}\Delta INV_{it} + \beta_{2t}\Delta GM_{it} + \beta_{3t}\Delta SGA_{it} + \beta_{4t}\Delta REC_{it}$.

	ΔINV	ΔGM	ΔSGA	ΔREC
(1)	(2)	(3)	(4)	(5)
Means across	−0.361	−1.062	−1.167	−0.271
years	(−2.30)[a]	(−3.20)	(−3.49)	(−1.34)
Pooled	−0.344	−0.670	−0.939	−0.278
sample	(−7.59)	(−8.64)	(−10.76)	(−4.65)

[a] t-statistics are in parentheses.

Regression coefficients, function $G(.)$ and market-adapted earnings are endogenously estimated from stock returns, reported earnings changes and four supplementary accounting signals: inventory valuation, gross margin, SG&A, and accounts receivable for 636 firms from 1990–2000.

Variable Definitions:

R_{it} = annual abnormal return, calculated by accumulating raw stock returns over the 12 months (from three months after the fiscal year begins until three months after the fiscal year ends minus the CRSP equally weighted monthly return accumulated for the same period); and

ΔE_{it} = annual change in earnings deflated by beginning of fiscal year share price.

ΔINV, ΔGM, ΔSGA, ΔREC are defined in Table 1.

−1.167 (−3.49), and −0.271 (−1.34), respectively, where t-statistics are given in parentheses. In addition, the estimated coefficients (t-values) for the pooled sample are −0.344 (−7.59), −0.670 (−8.64), −0.939 (−10.76), and −0.278 (−4.65), respectively, and these effects are all significant.[11]

The above significant and negative β coefficients demonstrate that market participants consider the first three fundamental accounting signals in forming their perceptions on future earnings, while results on accounts receivable are mixed. The findings also shed light on the relative weight of each signal as assigned by market participants in forming their expectations on future earnings. Specifically, the estimated weight assigned to news, as signaled through changes in gross margins and SG&A, is about three times greater than the weight assigned to news signaled through changes in the value of inventory. Consistent with the earlier studies, the estimated function $G(.)$ plotted in Figure 1 shows an S-shaped relationship between stock returns and MAE_{it}.

To gain further insights into both the nonlinearity and the supplementary accounting signals, we compare the SIM model with two models previously explored in the literature: the LT model and the DL model.

The LT Model—fundamental accounting signals (Lev and Thiagarajan 1993):

$$R_{it} = \alpha_t + \beta_{0t}\Delta E_{it} + \beta_{1t}\Delta INV_{it} + \beta_{2t}\Delta GM_{it} + \beta_{3t}\Delta SGA_{it} + \beta_{4t}\Delta REC_{it} + \varepsilon_{it}.$$

The DL Model—nonlinearity (Das and Lev 1994):

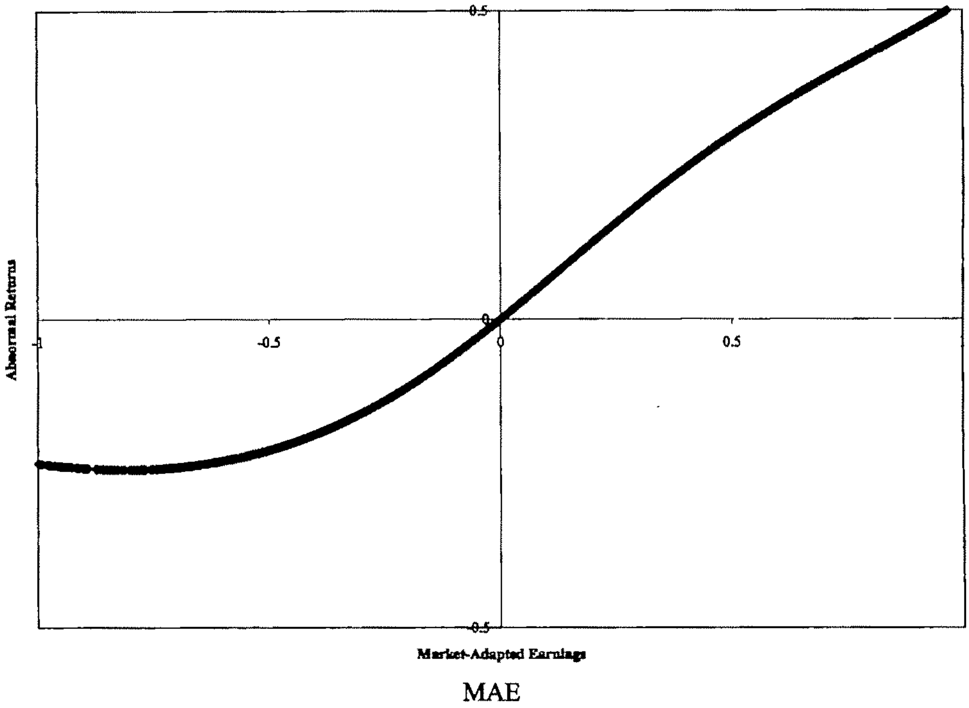
$$R_{it} = G(\Delta E_{it}) + \varepsilon_{it}.$$

---

[11] The t-statistics in Table 3 are not corrected for serial correlation or clustering by firms because such corrections are not available for single-index models (see Li and Racine 2007, Chapters 8 and 19).

FIGURE 1
Relationship between Abnormal Returns and Market-Adapted Earnings

Model: $R_{it} = G(MAE_{it})$, where $MAE_{it} = \Delta E_{it} + \beta_{1t}\Delta INV_{it} + \beta_{2t}\Delta GM_{it} + \beta_{3t}\Delta SGA_{it} + \beta_{4t}\Delta REC_{it}$.[a]
The figure plots function $G(.)$ and shows an S-shaped relationship between stock returns and MAE, 6360 firm-year observations, 1990–2000.



---

[a] The upper and lower 1 percent of the observations are truncated.

Because the LT model follows the linear specification with supplementary accounting signals, we compare it with SIM to infer the net contribution of nonlinearity in improving the Lev and Thiagarajan (1993) specification. Similarly, because the DL model emphasizes the nonlinear link between returns and earnings, but ignores supplementary accounting signals, we compare it with SIM to infer the net contribution from introducing supplementary accounting signals.

Table 4 presents the results of these comparisons. Specifically, on average, the explanatory power of the SIM model measured by adjusted R^2 is 40.5 percent greater than that of the DL model, and 58.9 percent greater than that of the LT model. In addition, the SIM model has a greater explanatory power for 9 of the 11 years compared with the DL model and for all 11 years compared with the LT model.

This improvement in explanatory power due to the SIM model ranges between 2.9 percent and 156.1 percent for the LT comparison and between −29.7 percent and 264.1 percent for the DL comparison. These results are consistent with Lev and Thiagarajan (1993, Tables 2 and 3) and Das and Lev (1994, Table 1), who also report considerable intertemporal variation.

TABLE 4
A Comparative Analysis of Adjusted R²[a]

DL Model: $R_{it} = G_t(\Delta E_{it}) + \varepsilon_{it}$

LT Model: $R_{it} = \alpha_t + \beta_{0t}\Delta E_{it} + \beta_{1t}\Delta INV_{it} + \beta_{2t}\Delta GM_{it} + \beta_{3t}\Delta SGA_{it} + \beta_{4t}\Delta REC_{it} + \varepsilon_{it}$

SIM: $R_{it} = G_t(MAE_{it}) + \varepsilon_{it}$,

where $MAE_{it} = \Delta E_{it} + \beta_{1t}\Delta INV_{it} + \beta_{2t}\Delta GM_{it} + \beta_{3t}\Delta SGA_{it} + \beta_{4t}\Delta REC_{it}$.

				Improvement (%)		
Year	**DL Model Adjusted R^2 %**	**LT Model Adjusted R^2 %**	**SIM Adjusted R^2 %**	**Model SIM over Model DL = [(4) − (2)] / (2)**	**Model SIM over Model LT = [(4) − (3)] / (3)**	**n**
(1)	(2)	(3)	(4)	(5)	(6)	(7)
1990	11.66	11.16	13.50	15.8	21.0	636
1991	6.60	8.13	8.67	31.4	6.6	636
1992	14.85	9.12	16.42	10.6	80.0	636
1993	19.85	18.77	32.98	66.1	75.7	636
1994	10.62	19.84	38.67	264.1	94.9	636
1995	11.10	8.71	8.96	(19.3)	2.9	636
1996	26.67	11.71	18.74	(29.7)	60.0	636
1997	11.68	5.17	13.24	13.4	156.1	636
1998	5.54	3.57	6.89	24.4	93.0	636
1999	9.21	7.44	10.24	11.2	37.6	636
2000	8.08	10.63	12.75	57.8	19.9	636
Average improvement				40.5	58.9	

[a] The sample includes 636 constant firms, 1990–2000.

Variable Definitions:

R_{it} = annual abnormal return, calculated by accumulating raw stock returns over the 12 months (from three months after the fiscal year begins until three months after the fiscal year ends minus the CRSP equally weighted monthly return accumulated for the same period); and

ΔE_{it} = annual change in earnings, deflated by beginning of fiscal year share price.

ΔINV, ΔGM, ΔSGA, ΔREC are defined in Table 1.

We next test the economic significance of the incremental explanatory power of supplementary accounting signals. To this end, we compare the nonlinear DL model with the SIM model using an F*-test.[12] The second column of Table 5 reports F*-statistics for testing the null hypothesis (the DL model is the appropriate specification) against the alternative hypothesis (SIM is better specified). The F*-statistics for the 9 out of 11 years reject the null at the $\alpha = 0.05$ level. In addition, the third column of Table 5 reports Smirnov statistics for testing the null hypothesis (the

---

[12] For simplicity, we followed the classical methodology to approximate an F-statistic and used $F^* = [\ (SSE_1 - SSE) / k)] / [SSE / (N - k - 1)$, where N = number of observations, SSE (SSE_1) = residual sum of squares for the five-variable model (earnings-only sample), and $k = 4$, the number of additional variables (Kmenta 1986, 417). We also computed the degrees of freedom for the appropriate matrices and used Cleveland and Devlin's (1988) approximation for an F-statistic. Similar results hold for both tests.

TABLE 5

Test of Alternative Specifications of the Returns-Earnings Relationship for 636 Constant Firms 1990–2000

DL Model: $R_{it} = G_t(\Delta E_{it}) + \varepsilon_{it}$
LT Model: $R_{it} = \alpha_t + \beta_{0t}\Delta E_{it} + \beta_{1t}\Delta INV_{it} + \beta_{2t}\Delta GM_{it} + \beta_{3t}\Delta SGA_{it} + \beta_{4t}\Delta REC_{it} + \varepsilon_{it}$
SIM: $R_{it} = G_t(\text{MAE}_{it}) + \varepsilon_{it}$,
where $MAE_{it} = \Delta E_{it} + \beta_{1t}\Delta INV_{it} + \beta_{2t}\Delta GM_{it} + \beta_{3t}\Delta SGA_{it} + \beta_{4t}\Delta REC_{it}$.

	H_0: DL is the Appropriate Specification H_1: SIM is the Appropriate Specification		H_0: LT is the Appropriate Specification H_1: SIM is the Appropriate Specification	
Year (1)	**F*-statistic**[a] (2)	**Smirnov Statistic**[b] (3)	**F-statistic**[a] (4)	**Smirnov Statistic**[b] (5)
1990	4.336 (0.0007)	0.057 (0.0181)	3.5750 (0.0015)	0.064 (0.0050)
1991	13.412 (0.0000)	0.047 (0.0741)	1.4191 (0.1990)	0.069 (0.0020)
1992	3.922 (0.0017)	0.085 (0.0001)	9.8048 (0.0000)	0.131 (0.0000)
1993	31.331 (0.0000)	0.039 (0.2151)	22.7074 (0.0000)	0.027 (0.7100)
1994	73.080 (0.0000)	0.074 (0.0006)	31.4839 (0.0000)	0.052 (0.0400)
1995	NA[c]	0.050 (0.0478)	1.1180 (0.3501)	0.053 (0.0350)
1996	NA[c]	0.060 (0.0111)	4.6068 (0.0000)	0.108 (0.0000)
1997	3.672 (0.0028)	0.127 (0.0000)	10.5024 (0.0000)	0.131 (0.0000)
1998	3.488 (0.0041)	0.045 (0.0975)	3.9167 (0.0003)	0.083 (0.0001)
1999	2.927 (0.0127)	0.131 (0.0000)	3.9286 (0.0005)	0.182 (0.0000)
2000	9.453 (0.0000)	0.189 (0.0000)	3.6413 (0.0022)	0.134 (0.0000)

---

[a] For simplicity, we followed the classical methodology to approximate an F*-statistic and used $F^* = [(SSE_1 - SSE)/(k)SSE/(N-k-1)]$, where N = number of observations, $SSE(SSE_1)$ = residual sum of squares for the five-variable model (earnings-only sample), and $k = 4$, the number of additional variables (Kmenta 1986, 417). We also computed the degrees of freedom for the appropriate matrices and used Cleveland and Devlin's (1988) approximation for an F-statistic. Similar results hold for both tests.

[b] The two sample Smirnov tests (also called the Kolmogorov-Smirnov test) follow Lindgren (1968, 494).

[c] The residual sum of squares for the SIM is higher than for the DL Model, suggesting that the DL Model has better explanatory power than the SIM for 1995 and 1996.

(continued on next page)

TABLE 5 (continued)

Cell entries in column 2 (4) report an F* (F)-statistic that tests for the null hypothesis that the DL (LT) model is the appropriate specification, against the alternative that the SIM is better specified. Numbers in parentheses represent the corresponding p-values. A significant F-statistic implies a rejection of the null.

Cell entries in column 3 (5) report a Smirnov statistic that tests for the null hypothesis that the specification of the DL (LT) model and the SIM are equivalent estimations, against the alternative that they are different estimations. Numbers in parentheses represent the corresponding p-values. A significant Smirnov statistic implies a rejection of the null.

specification of the DL model and SIM are equivalent) against the alternative hypothesis (they are different). Smirnov statistics for the 8 out of 11 years are significant at the $\alpha = 0.05$ level, thus rejecting the null hypothesis. The above evidence demonstrates that, beyond nonlinearity, the supplementary accounting signals contain meaningful information.

We further test the incremental explanatory power of nonlinearity given multiple accounting variables. We use F-statistics to test for the null hypothesis (i.e., the LT model is the appropriate specification) against the alternative hypothesis (i.e., SIM is better specified). The fourth column of Table 5 reports F-statistics, which are significant for 9 of the 11 years, suggesting that we can reject the null at the $\alpha = 0.05$ level. The fifth column reports a Smirnov statistic for testing the null hypothesis (the specifications of the LT model and SIM are equivalent) against the alternative (i.e., they are different). Smirnov statistics for 10 of the 11 years are significant at the $\alpha = 0.05$ level and. Hence. we reject the null hypothesis. Consequently, this evidence indicates that, beyond multiple accounting signals, nonlinearity provides meaningful information.

To assess robustness, we replicate the above analyses by using eight supplementary signals in Lev and Thiagarajan (1993)—that is, including four additional signals (changes in capital expenditures, effective tax rate, order backlog, and labor force)—and by using the sampling criteria used by Abarbanell and Bushee (1997). We find that three of the four additional signals are insignificant (only order backlog was significant). In addition, across 11 years, we find that on average the explanatory power of the SIM model as measured by adjusted R^2 is 30.3 percent greater than that of the DL model, and 41.4 percent greater than that of the LT model. In sum, the evidence suggests that both nonlinearity and supplementary accounting signals contribute to the improved specification of SIM. We next examine the predictive power of market-adapted earnings.

IV. OUT-OF-SAMPLE EARNINGS PREDICTION

In this section, we compare one-year-ahead forecasts from the market-adapted earnings, *MAE**, with those obtained from the random-walk model and the accounting-based model (ABM) proposed by Abarbanell and Bushee (1997).

The ABM Model—accounting-based model (Abarbanell and Bushee 1997)

$$\Delta E_{i,t+1} = \alpha_t + \beta_{0t}\Delta E_{it} + \beta_{1t}\Delta INV_{it} + \beta_{2t}\Delta GM_{it} + \beta_{3t}\Delta SGA_{it} + \beta_{4t}\Delta REC_{it} + \varepsilon_{i,t}.$$

To study out-of-sample earnings prediction, we first estimate the regression coefficients based on the accounting information reported for fiscal years t and $t-1$. Next, we use the estimated model coefficients to forecast earnings change in $t+1$ for each firm i, based on its accounting signals reported for the fiscal year t. Accordingly, we need two years of data for out-of-sample forecasts.

In ABM, the average estimated effects across years for changes in inventory valuation, changes in gross margins, changes in SG&A, and changes in accounts receivable are −0.040 (−1.880), −0.016 (−2.240), −0.045 (−2.051), −0.068 (−0.283), respectively, where t-statistics are given in parentheses. Note that these four estimated effects in ABM differ significantly from the corresponding estimated coefficients in SIM (see the first row of Table 3), leading to different forecasting performance.

To compare prediction accuracy across *MAE**, random-walk and ABM models, we analyze the sample from 1992 to 2001. Using *MAE** to predict out-of-sample earnings change, we employ information observed in year t to forecast earnings change in year $t+1$. The incremental out-of-sample earnings prediction power of *MAE** over the two benchmark models is evaluated based on the potential increase in predictive accuracy. The absolute percentage forecast error is defined as the percentage difference between actual and forecasted earnings divided by the actual earnings (firm subscript suppressed):

$$\begin{aligned}\text{Earnings forecast error} &= \left|\frac{\text{Actual} - \text{Forecasted}}{\text{Actual}}\right| = \left|\frac{E_{t+1} - \text{Forecasted } E_{t+1}}{E_{t+1}}\right| \\ &= \left|\frac{E_{t+1} - (E_t + \text{Forecasted } \Delta E_{t+1})}{E_{t+1}}\right| = \left|\frac{\Delta E_{t+1} - \text{Forecasted } \Delta E_{t+1}}{E_{t+1}}\right|. \qquad (4)\end{aligned}$$

This measure of earnings forecast error has been used in earlier studies (e.g., BLM; Collins et al. 1987; Elgers and Murray 1992).

Table 6 presents the absolute earnings forecast errors obtained from the three models. Because percentage forecast errors can become quite large when scaled by relatively small actual earnings values, as in Collins et al. (1987), we report the median rather than the mean. Table 6 shows that the median *MAE** forecast error is smaller than the median random-walk forecast errors in nine out of the ten years. For the pooled sample, the median *MAE** forecast error is 0.273, which is 20.9 percent lower than the median random-walk forecast error, 0.345. Furthermore, 56.1 percent of the pooled sample observations have a lower absolute earnings forecast error for *MAE** than that for the random-walk model (t-statistic = 9.781).[13] Hence *MAE** outperforms the random-walk model.

Similarly, Table 6 shows that *MAE** yields lower forecast errors than the ABM. The median *MAE** forecast error is smaller than the median forecast error of the ABM in nine out of the ten years. For the pooled sample, the median *MAE** forecast error is 0.273, which is 17.0 percent lower than the median ABM forecast error, 0.329. In addition, 57.7 percent of the pooled sample observations have a lower absolute earnings forecast error for *MAE** than that for the ABM (t-statistic = 12.328). Hence *MAE** outperforms the accounting-based model.

Across the three models, the evidence indicates that employing the SIM model to extract forward-looking information from stock returns results in a higher level of accuracy than either the random-walk or the ABM models. In other words, the accuracy of earnings forecasts enhances when we utilize information contained in stock returns.[14]

In the rest of this section, we compare the performance of *MAE** with analysts' earnings forecasts; in the subsequent section, we present results when no analyst coverage is available. To this end, we obtain analysts' consensus earnings forecasts from I/B/E/S. Specifically, we use the consensus forecasts of annual earnings announced in the fourth month after the start of the fiscal year to keep a contemporaneous analysis with no timing advantage. Firm-years observations with

---

[13] We use the normal approximation of the binomial probabilities to test the hypothesis that the probability of a lower error is 0.5 (see BLM, 24).

[14] When stock returns are positive (i.e., good news), further analyses reveal that the accuracy of *MAE** increases (median absolute forecast error = 0.206); when stock returns are negative (i.e., bad news), *MAE** accuracy decreases (median absolute forecast error = 0.429). One reason for larger forecast errors under bad news is that earnings realizations exhibit large extreme values, partly due to write-offs and nonrecurring items.

TABLE 6
Out-of-Sample Earnings Prediction
MAE* versus Random-Walk and Accounting-Based Model

	Random-Walk (*RW*)			Market-Adapted Earnings (*MAE**)			Accounting-Based Model (*ABM*)		
Predicted Year (1)	Median Absolute Error[a] (2)	Percent times *MAE** has Lower Error[c] (3)	Median Difference[b] *RW* − *MAE** (4)	Median Improvement Over *RW* (5) = [(2) − (6)] / (2)	Median Absolute Error[a] (6)	Median Improvement Over the *ABM* (7) = [(8) − (6)] / (8)	Median Absolute Error[a] (8)	Percent times MAE* has Lower Error[c] (9)	Median Difference[b] *ABM* − *MAE** (10)
1992	0.299	0.524	0.017	16.8	0.249	14.1	0.290	0.561	0.025
		(1.190)						(3.093)	
1993	0.415	0.601	0.103	33.4	0.277	31.8	0.406	0.613	0.076
		(5.076)						(5.710)	
1994	0.395	0.616	0.121	42.6	0.227	−15.8	0.196	0.403	−0.038
		(5.869)						(−4.917)	
1995	0.374	0.590	0.079	43.2	0.213	20.2	0.267	0.555	0.022
		(4.520)						(2.776)	
1996	0.298	0.571	0.048	31.1	0.205	26.0	0.277	0.623	0.065
		(3.569)						(6.186)	
1997	0.325	0.552	0.037	20.8	0.258	22.5	0.333	0.619	0.051
		(2.617)						(6.027)	
1998	0.335	0.550	0.025	18.3	0.274	18.5	0.336	0.583	0.034
		(2.538)						(4.203)	
1999	0.371	0.560	0.044	14.0	0.319	15.8	0.379	0.588	0.052
		(3.014)						(4.441)	
2000	0.345	0.577	0.058	22.3	0.268	26.8	0.366	0.626	0.068

(continued on next page)

TABLE 6 (continued)

	Random-Walk (*RW*)			Market-Adapted Earnings (*MAE**)			Accounting-Based Model (*ABM*)		
Predicted Year (1)	Median Absolute Error[a] (2)	Percent times *MAE** has Lower Error[c] (3)	Median Difference[b] *RW* − *MAE** (4)	Median Improvement Over *RW* (5) = [(2) − (6)] / (2)	Median Absolute Error[a] (6)	Median Improvement Over the *ABM* (7) = [(8) − (6)] / (8)	Median Absolute Error[a] (8)	Percent times MAE* has Lower Error[c] (9)	Median Difference[b] *ABM* − *MAE** (10)
		(3.886)						(6.334)	
2001	0.327	0.473	−0.032	−14.6	0.374	14.4	0.437	0.601	0.072
		(−1.348)						(5.076)	
All	0.345	0.561	0.049	20.9	0.273	17.0	0.329	0.577	0.038
		(9.781)						(12.328)	

---

[a] Absolute earnings forecast error is the absolute value of the percentage difference between actual and forecasted earnings divided by actual earnings.

[b] The difference in absolute earnings forecast errors is computed for all observations in each year and the median is reported.

[c] Percent of firm-year observations with absolute earnings forecast error lower for market-adapted earnings than for the alternative model. Numbers in parentheses are t-statistics for testing the null hypothesis that the probability of a lower error is 0.5 using a normal approximation of the binomial probabilities.

analyst coverage comprise 66.2 percent of our sample (4213 out of 6360). The analyst earnings forecast error is computed using Equation (4), where firms' actual earnings are obtained from I/B/E/S for comparability with the forecast (see Richardson et al. 2004, 896).

Table 7 presents the comparative results for observations with analyst coverage—see the first row. The median absolute forecast error of *MAE** is 21.0 percent higher than that for the analysts' forecasts. Moreover, analysts forecasts have smaller error than *MAE** on 53.2 percent (=100 − 46.8) of the observations (t-statistic = −4.128). This finding indicates that analysts provide investors with more accurate earnings forecasts than *MAE**, and it is consistent with the extant literature (e.g., Fried and Givoly 1982; Brown et al. 1987; Banker and Chen 2006).

Furthermore, we examine the analysts' advantage over *MAE** in low versus high information environments as measured by the number of analysts covering each firm (see the second and third rows in Table 7). In high (low) coverage, analysts' forecasts outperform *MAE** by 22.2 percent (16.6 percent). Analysts do better than *MAE** because their forecasts are based on all available information, not just financial variables. In contrast, in low information environment, the performance of both analysts and *MAE** degrades because fundamentals are likely to be more volatile. Overall, analysts' incremental usefulness over *MAE** is more pronounced in rich-information environments.

TABLE 7

Out-of-Sample Earnings Prediction: *MAE** versus Analyst Earnings Forecasts

	Analyst Earnings Forecasts (*AF*)			**Market-Adapted Earnings (*MAE**)**	
Group (1)	**Median Absolute Error**[a] (2)	**Percent times *MAE** Has Lower Error**[c] (3)	**Median Difference**[b] ***AF* − *MAE**** (4)	**Median Improvement Over *AF*** (5) = [(2) − (6)] / (2)	**Median Absolute Error**[a] (6)
ALL firm-year observations with analyst coverage	0.203	0.468 (−4.128)	−0.028	−21.0	0.246
Low coverage	0.239	0.495 (−0.437)	−0.004	−16.6	0.278
High[d] coverage	0.174	0.442 (−5.371)	−0.041	−22.2	0.213

---

[a] Absolute earnings forecast error is the absolute value of the percentage difference between actual and forecasted earnings divided by actual earnings.

[b] The difference in absolute earnings forecast errors is computed for all observations in each year and the median is reported.

[c] Percent of firm-year observations with absolute earnings forecast error lower for market-adapted earnings than that for the alternative model. Numbers in parentheses are t-statistics for testing the null hypothesis that the probability of a lower error is 0.5 using a normal approximation of the binomial probabilities.

[d] Analyst coverage is high when the number of analysts is equal to or above its median (=8).

Finally, we assess the relative advantage of *MAE** over the random-walk and accounting-based earnings forecasts as the richness of the information environment varies. We expect a higher relative advantage of *MAE** over the random-walk and the accounting-based earnings forecasts when more information is available. Table 8 shows that *MAE** improves the random-walk model (ABM) by 26.1 percent (20.6 percent) under high coverage and by 10.4 percent (10.7 percent) under low coverage. Thus the incremental advantage of *MAE** over both the random-walk and ABM models is higher in richer information environments (i.e., high coverage) because it extracts information from stock prices, which incorporate more information in richer information environments. The next section examines whether *MAE** offers better predictions for firms with no analyst coverage.

V. FIRMS WITH NO ANALYST COVERAGE

When analysts' forecasts are not available, researchers use potentially inferior proxies for market expectations of future earnings. As in the previous section, we compare the predictive performance of *MAE** with that of the random-walk and ABM models for firms with no analyst coverage. Results reported in the first row of Table 8 indicate that *MAE** outperforms both the random-walk and ABM models. Specifically, the median *MAE** absolute forecast error is 14.4 percent (12.0 percent) lower than the median random-walk (ABM) absolute forecast error. In addition, *MAE** outperforms the random-walk model (ABM) on 55.2 percent (53.6 percent) of the observations (t-statistic is 2.796 (3.324)).[15]

The reason for the superiority of *MAE** over accounting-based earnings forecasts for the firms with no analyst coverage is due to its ability to exploit information contained in stock prices. In other words, *MAE** yields improved price-based forecasts over accounting-based forecasts because it utilizes a richer information set. Thus *MAE** is of most useful when analysts' earnings forecasts are not available, because investors and researchers cannot benefit from alternative earnings forecasts.

VI. SUMMARY

Understanding how market participants form earnings expectations has long been a subject of interest to accounting researchers. This paper introduces a new estimation approach, SIM regression, for extracting forward-looking information from stock returns. We propose and estimate market-adapted earnings, which estimates market expectations of future earnings conditioned on stock returns and multiple accounting signals. We demonstrate an economically meaningful predictive advantage of *MAE** over both the random-walk model and ABM. In particular, *MAE** is shown to be useful for a class of firms with no analyst following. Hence, researchers can employ market-adapted earnings as a proxy for market expectations of future earnings for firms with no analyst coverage.

---

[15] As a robustness check, we replicate the analysis using a less restrictive sample. Specifically, we utilize all firm-year observations with available data for our variables from Compustat and CRSP. To avoid the small deflator problem, we consider stock prices to be at least five dollars (e.g., Lim 2001), obtaining 29,498 observations for 5,033 firms. The less restrictive sample consists of 15,195 observations with no analyst coverage (51.5 percent of the sample observations in contrast with 33.8 percent in the constant-firms sample). Results (not reported here) indicate that *MAE** is more accurate than the random-walk model (*ABM*) by 8.6 percent (8.0 percent) under no analyst coverage. Furthermore, the absolute forecast error for *MAE** is lower among 54.2 percent (54.0 percent) of the observations than that for the random-walk model (*ABM*) with t-statistic = 10.354 (9.861). Thus, in the less restrictive sample, these findings confirm the predictive advantage of *MAE** over both the random-walk model and *ABM*. We thank an anonymous referee for suggesting this analysis.

TABLE 8

Out-of-Sample Earnings Prediction

*MAE** versus Random-Walk and Accounting-Based Model for Firms with No, Low, and High Analyst Coverage

	Random Walk (*RW*)			Market-Adapted Earnings (*MAE**)			Accounting Based Model (*ABM*)			
Group	**Median Absolute Error**[a]	**Percent times *MAE** Has Lower Error**[c]	**Median Difference**[b] ***RW* − *MAE****	**Median Improvement Over *RW***	**Median Absolute Error**[a]	**Median Improvement Over the *ABM***	**Median Absolute Error**[a]	**Percent times *MAE** Has Lower Error**[c]	**Median Difference**[b] ***ABM* − *MAE****	**n**
(1)	(2)	(3)	(4)	(5) = [(2) − (6)] / (2)	(6)	(7) = [(8) − (6)] / (8)	(8)	(9)	(10)	(11)
No coverage	0.396	0.552 (2.796)	0.014	14.4	0.339	12.0	0.386	0.536 (3.324)	0.013	2147
Low coverage[c]	0.310	0.569 (3.624)	0.021	10.4	0.278	10.7	0.311	0.569 (6.331)	0.038	2098
High coverage[d]	0.288	0.627 (6.759)	0.038	26.1	0.213	20.6	0.335	0.581 (11.720)	0.038	2115

---

[a] Absolute earnings forecast error is the absolute value of the percentage difference between actual and forecasted earnings divided by actual earnings.

[b] The difference in absolute earnings forecast errors is computed for all observations in each year and the median is reported.

[c] Percent of firm-year observations with absolute earnings forecast error lower for market-adapted earnings than that for the alternative model. Numbers in parentheses are t-statistics for testing the null hypothesis that the probability of a lower error is 0.5 using a normal approximation of the binomial probabilities.

[d] Analyst coverage is high when the number of analysts is equal to or above its median (=8).

APPENDIX
SINGLE-INDEX MODEL ESTIMATION

Here, for a given year t, we describe the estimation of the single-index model:

$$R_i = G(MAE_i) + \varepsilon_i,$$

where $MAE_i = \Delta E_i + \beta_1 \Delta INV_i + \beta_2 \Delta GM_i + \beta_3 \Delta SGA_i + \beta_4 \Delta REC_i$, and R_i denotes the dependent variable and ε_i is the normal error term with zero mean and constant variance.

Let the vector X_i contain the five regressors ΔE_i, ΔINV_i, ΔGM_i, ΔSGA_i, and ΔREC_i. We first compute the usual covariance matrix:

$$\hat{\Sigma}_x = \frac{1}{N}\sum_{i=1}^{N} (X_i - \bar{X})(X_i - \bar{X})', \tag{A1}$$

where X_i' denotes a row for the ith firm, and $\bar{X}$ contains the means of the five variables across all N firms.

Next, we create a matrix (R, X) and sort it by the increasing values of R_i. We partition the *sorted* (R, X) matrix into H groups or slices, and we denote each sub-matrix of regressors in slice h by X_h, where $h = 1,\ldots,H$. Slicing captures the nonlinearity of the link function $G(.)$ without the need to know its exact shape, thus mitigating the risk of specification error (see Duan and Li 1991).

We compute the sample means of the regressors for each group X_h across the respective firms in the slice h and denote them by $\bar{X}_h$. The weighted average across all H slices yields the covariance matrix:

$$\hat{\Sigma}_\eta = \sum_{h=1}^{H} \hat{p}_h(\bar{X}_h - \bar{X})(\bar{X}_h - \bar{X})', \tag{A2}$$

where $\hat{p}_h$ is the proportion of firms in slice h.

Then, to estimate β, we extract the principal eigenvector γ of the generalized eigenvalue decomposition problem:

$$\hat{\Sigma}_\eta \gamma = \lambda \hat{\Sigma}_x \gamma, \tag{A3}$$

where λ is the largest eigenvalue. We also obtain the standard errors of $\hat{\beta}$ (see Chen and Li 1998, 297) by taking the squared root of the diagonal of the matrix:

$$\frac{1-\hat{\lambda}}{\hat{\lambda}} N^{-1} \hat{\Sigma}_x^{-1}. \tag{A4}$$

Using these estimated parameters and their standard errors, we can thus compute the t-values to determine the significant effects at the 95 percent confidence level.

Finally, we normalize the first element of $\hat{\beta}$ to unity and construct the Single Index $z_i = X_i'\hat{\beta}$ to estimate the unknown function $\hat{G}$ by applying the standard local polynomial regression to the model $R_i = G(z_i) + \varepsilon_i$ (see Simonoff 1996; Das and Lev 1994). The local polynomial regression requires a selection of a bandwidth parameter, which is set to unity. For software, see note at: http://recanati.tau.ac.il/_Uploads/20SIM.pdf.

REFERENCES

Abarbanell, J. S., and B. J. Bushee. 1997. Fundamental analysis, future earnings, and stock returns. *Journal of Accounting Research* 35 (1): 1–24.

——, and ——. 1998. Abnormal returns to a fundamental analysis strategy. *The Accounting Review* 73 (1): 19–45.

Ait-Sahalia, Y., and M. W. Brandt. 2001. Variable selection for portfolio choice. *The Journal of Finance* 56: 1297–1351.

Ayers, B. C., and R. N. Freeman. 2000. Why do large firms' prices anticipate earnings earlier than small firms' prices? *Contemporary Accounting Research* 17 (2): 191–212.

——, and ——. 2003. Evidence that analyst following and institutional ownership accelerates the pricing of future earnings. *Review of Accounting Studies* 8: 47–67.

Banker, R., and L. Chen. 2006. Predicting earnings using a model based on cost variability and cost stickiness. *The Accounting Review* 81: 285–307.

Beaver, W. H., R. Lambert, and D. Morse. 1980. The information content of security prices. *Journal of Accounting and Economics* 2: 3–28.

——, ——, and S. G. Ryan. 1987. The information content of security prices—A second look. *Journal of Accounting and Economics* 9: 139–157.

——, M. L. McAnally, and C. H. Stinson. 1997. The information content of earnings and prices: A simultaneous equations approach. *Journal of Accounting and Economics* 23: 53–81.

Beneish, M. D., and C. R. Harvey. 1998. Measurement error and nonlinearity in the earnings-returns relation. *Review of Quantitative Finance and Accounting* 11: 219–247.

Brown, L. D. 1993. Earnings forecasting research: Its implications for capital market research. *International Journal of Forecasting* 9: 295–320.

——, R. L. Hagerman, P. A. Griffin, and M. E. Zmijewski. 1987. Security analyst superiority relative to univariate time-series models in forecasting quarterly earnings. *Journal of Accounting and Economics* 9: 61–87.

Chen, C. H., and K. C. Li. 1998. Can SIR be as popular as multiple linear regression? *Statistica Sinica* 8: 289–316.

Cheng, C. S. A., W. S. Hopewood, and J. C. McKeown. 1992. Non-linearity and specification problems in unexpected earnings response regression models. *The Accounting Review* 67 (3): 579–598.

Cleveland, W. S., and S. J. Devlin. 1988. Locally weighted regression: An approach to regression analysis by local fitting. *Journal of the American Statistical Association* 83 (403): 596–610.

Collins, D. W., S. P. Kothari, and J. D. Rayburn. 1987. Firm size and the information content of prices with respect to earnings. *Journal of Accounting and Economics* 9: 111–138.

Cready, W. M., D. H. Hurtt, and J. A. Seida. 2000. Applying reverse regression techniques in earnings-return analyses. *Journal of Accounting and Economics* 30: 227–240.

Das, S., and B. Lev. 1994. Nonlinearities in the returns-earnings relation: Tests of alternative specifications and explanations. *Contemporary Accounting Research* 11 (1): 353–379.

Duan, N., and K-C. Li. 1991. Slicing regression: A link-free regression method. *Annals of Statistics* 19: 505–530.

Elgers, P. T., and D. Murray. 1992. The relative and complementary performance of analyst and security-price-based measures of expected earnings. *Journal of Accounting and Economics* 15 (2): 303–316.

Fama, E. F., and K. R. French. 2000. Forecasting profitability and earnings. *Journal of Business* 73 (2): 161–175.

Freeman, R. N. 1987. The association between accounting earnings and security returns for large and small firms. *Journal of Accounting and Economics* 9 (2): 195–228.

——, and S. Y. Tse. 1992. A nonlinear model of security price responses to unexpected earnings. *Journal of Accounting Research* 30 (2): 185–209.

Fried, D., and D. Givoly. 1982. Financial analysts' forecasts of earnings: A better surrogate for market expectations. *Journal of Accounting and Economics* 11: 1–31.

Greene, W. H. 2003. *Econometric Analysis*. Englewood Cliffs, NJ: Prentice Hall.

Horowitz, J. L. 1998. *Semiparametric Methods in Econometrics*. New York, NY: Springer.

Jiambalvo, J., S. Rajgopal, and M. Venkatachalam. 2002. Institutional ownership and the extent to which stock prices reflect future earnings. *Contemporary Accounting Research* 19: 117–145.

Kmenta, J. 1986. *Elements of Econometrics*. 2nd edition. New York, NY: Macmillan Publishing Co.

Kothari, S. P. 1992. Price-earnings regressions in the presence of prices leading earnings. *Journal of Accounting and Economics* 15 (2–3): 173–202.

———, and R. G. Sloan. 1992. Information in prices about future earnings. *Journal of Accounting and Economics* 15 (2–3): 143–171.

———. 2001. Capital markets research in accounting. *Journal of Accounting and Economics* 31: 105–231.

Lev, B., and R. Thiagarajan. 1993. Fundamental information analysis. *Journal of Accounting Research* 31 (2): 190–215.

Li, K. C. 1991. Sliced inverse regression for dimension reduction. *Journal of the American Statistical Association* 86: 316–342.

Li, Q., and J. S. Racine. 2007. *Nonparametric Econometrics*. Princeton, NJ: Princeton University Press.

Lim, T. 2001. Rationality and analyst forecast bias. *The Journal of Finance* 56: 369–385.

Lindgren, B. W. 1968. *Statistical Theory*. New York, NY: Macmillan Publishing Co.

Naik, P. A., and C. L. Tsai. 2001. Single-index model selections. *Biometrika* 88 (3): 821–832.

O'Brien, P. 1988. Analysts' forecasts as earnings expectations. *Journal of Accounting and Economics* 10: 53–83.

Ou, J. A., and S. H. Penman. 1989a. Financial statement analysis and the prediction of stock returns. *Journal of Accounting and Economics* 11: 295–329.

———, and ———. 1989b. Accounting measurement, price-earnings ratio, and the information content of security prices. *Journal of Accounting Research* 27 (Supplement): 111–144.

———. 1990. The information content of nonearnings accounting numbers as earnings predictors. *Journal of Accounting Research* 28 (1): 144–163.

Penman, S. H. 1998. Combining earnings and book value in equity valuation. *Contemporary Accounting Research* 15 (3): 291–324.

Rajgopal, S., T. Shevlin, and M. Venkatachalam. 2003. Does the stock market fully appreciate the implications of leading indicators for future earnings? Evidence from order backlog. *Review of Accounting Studies* 8: 461–492.

Richardson, S., S. H. Teoh, and P. D. Wysocki. 2004. The walk-down to beatable analyst forecasts: The role of equity issuance and insider trading incentives. *Contemporary Accounting Research* 21 (4): 885–924.

Simonoff, J. S. 1996. *Smoothing Methods in Statistics*. New York, NY: Springer.

THE ACCOUNTING REVIEW
Vol. 83, No. 4
2008
pp. 1125–1146

American Accounting Association
DOI: 10.2308/accr.2008.83.4.1125

The Effects of Perceived Fairness and Communication on Honesty and Collusion in a Multi-Agent Setting

Yue Zhang
Northeastern University

ABSTRACT: This study examines how two factors, the agents' perceptions regarding the fairness of the principal and inter-agent communication, affect agents' behaviors under a peer reporting system. Analytical models show that when agents can observe each other's actions and local signals, a peer reporting system with a verification mechanism (using one agent's information to verify the other's) and a reward for truthful whistleblowing can induce agents to report honestly and thereby help the principal achieve the first-best outcome. However, behavioral research suggests that the agents' perception regarding the fairness of the principal, as well as communication among agents, may affect how honestly agents report. The results of my experiment show that, under a peer reporting system with a high reward for whistleblowing, the agents' perception regarding the fairness of the principal positively affects the agents' reporting honesty and negatively affects their explicit attempts at collusion. Communication between agents decreases their reporting honesty when the principal is perceived as unfair, but not when the principal is perceived as fair.

Keywords: *perceived fairness; communication; peer reporting; collusion; honesty.*

Data Availability: *The experimental data are available for purposes of replication. Please contact the author.*

I. INTRODUCTION

Eliciting agents' private information is an important topic in the management accounting literature. Research in this area typically focuses on a one-principal, one-agent setting in which the agent possesses local information that is unknown to the principal. In practice, however, budgeting often takes place in multidivisional firms and involves interactions among

---

This study is based on my dissertation at University of Pittsburgh. I am indebted to the advice and encouragement from my committee: Jacob Birnberg (Chair), Harry Evans, Vicky Hoffman, Donald Moser, and Kristy Towry. I gratefully acknowledge the helpful comments and suggestions from two anonymous reviewers, Alexander Brüggen, Chee Chow, Marlys Lipe, George Loewenstein, Mario Maletta, Margie Platt, Tim Rupert, Arnie Wright, and workshop participants at University of Pittsburgh, Northeastern University, University of New Hampshire, San Diego State University, the 2005 AAA Ohio Regional Meeting, and the 2006 MAS Conference. I thank Tünde Kovacs and Ph.D. students at University of Pittsburgh for their help in administering the experiments. I appreciate the financial support from the Jacob Birnberg Recognition fund and the Dean's Distinguished Research Fellowship from the Katz Graduate School of Business.

Editor's note: This paper was accepted by Marlys Gascho Lipe.

Submitted: August 2006
Accepted: January 2008
Published Online: July 2008

multiple agents (Arya et al. 1996). As a result, agents often can observe each other's local production information, although such information may be costly for the principal to obtain. This richer setting presents the principal with a control opportunity. If the principal can successfully elicit information possessed by one agent about the other, then the principal can greatly improve his/her contractual position at a relatively low cost.

Several analytical modeling papers have investigated control issues in this type of setting (Demski and Sappington 1984; Demski et al. 1988; Ma 1988; Fischer and Hughes 1997). The general model in these papers is one in which each agent observes the other agent's action or private information and truthfully reports it to the principal. The agents are compensated based on their peer's report. In this study, this type of incentive system is referred to as a "peer reporting system." Ma (1988) proposes a typical example of a peer reporting system. Ma's (1988) system is particularly appealing since it demonstrates conditions under which the principal can achieve the first-best result (Towry 2003). Ma (1988) originally investigates a moral hazard problem. By logical extension, the model can also be applied to an information asymmetry setting and facilitate the ability of the principal to enforce truthful budgetary reporting from the agents.

The current study investigates how two factors, the agents' fairness perception of the principal and inter-agent communication, affect the honesty of agents' behaviors under a peer reporting system.[1] The key feature of Ma's (1988) model is that it provides a monetary reward for truthful whistleblowing. Given the reward, a wealth-maximizing agent will always prefer to truthfully blow the whistle on a lying peer. Anticipating that any lie will be turned in, no agent will lie to begin with. However, behavioral theories and evidence suggest that people are often reluctant to blow the whistle on others despite monetary rewards for doing so. Behavioral theories further suggest that the agents' honesty in reporting their own information and their willingness to blow the whistle on a lying peer are systematically affected by their fairness perception of the principal. Additionally, when agents have the opportunity to communicate with each other, whether they will exploit their communication ability to collude against the principal depends on the agents' fairness perception of the principal.[2] Specifically, communication between agents may decrease their reporting honesty and whistleblowing when the principal is perceived as unfair, but not when the principal is perceived as fair.

This study extends analytic research on incentive contracts designed for multi-agent environments by experimentally investigating how social factors affect the ability of such contracts to elicit honesty in agents' reporting. This study fits into the recent stream of research that analyzes control systems in context and melds theories from both economics and psychology to investigate accounting issues (Luft 1997; Evans et al. 2001; Fisher et al. 2002; Towry 2003; Rankin et al. 2003; Evans and Moser 2004; Hannan 2005). The most relevant literature to the current study is Towry (2003), which examines the use of peer reporting in incentive contracting and suggests that the psychological attachment between agents (as reflected by team identity) can impact the effectiveness of peer reporting. While Towry (2003) does not examine the principal's role, the current study suggests that the principal can have a significant impact on peer reporting. This is because under the peer reporting system, agents have to make a choice between two competing alternatives: to collude with the other agent or to blow the whistle. In such a situation, agents' choices can be systematically affected by how they perceive the principal and how motivated they are to be honest to the principal. The current study allows the principal to play an active role in designating a wage for the agents and shows that the agents' perceived fairness of the principal affects their reporting honesty under the peer reporting system. In doing so, this study demonstrates the importance of examining incentive systems in multi-person environments and the importance of considering contextual factors in incentive design.

---

[1] In this paper, the agents' fairness perception of the principal is based on the wage offered to them by the principal. Section III discusses this further. Inter-agent communication is "cheap talk," i.e., the costless, non-binding promises made by players in a strategic game.

[2] Collusion refers to coordination among the agents that is not in the principal's best interest. In this study, collusion specifically refers to the case where both agents agree to overstate their costs and cover for each other.

In addition, this study provides insights into the role of inter-agent communication in the setting of interest. In business practice, agents can acquire other agents' private information not only through direct communication, but also through job rotation, or through managing similar businesses that experience common exogenous shocks. These agents who can observe each other's information may have differential levels of communication among themselves. This study examines whether variation of inter-agent communication impacts agents' honesty under a peer reporting system. To operationalize the variation of communication in the strongest way possible, this experiment consists of a no-communication condition and a communication condition. The no-communication condition serves as a baseline.

I conducted an experiment with triads consisting of a principal and two agents. The agents report to the principal under a peer reporting system. The experiment adopts a 2 × 2 (Agent Communication × Wage) design. Agents' fairness perception is measured by asking the principal to choose a wage (500 liras or 1000 liras) for the agents and also by asking the agents to answer in the post-experimental questionnaire: "How fair did you perceive the principal to be when s/he offered you a 500 (1000) lira wage?"

Results show that despite the high reward for whistleblowing, agents report less honestly when they perceive the principal as unfair versus fair. In addition, communication between agents reduces their reporting honesty when the principal is perceived as unfair, but not when the principal is perceived as fair.

The remainder of this paper is organized as follows: The next section reviews the relevant literature and develops the hypotheses. Section III describes the research design. Section IV presents the results. The final section discusses the results and their implications.

II. THEORIES AND HYPOTHESES

Low Information Asymmetry among Agents and the Peer Reporting System

Due to job rotations, similarities in work environments, cooperation on interrelated tasks, etc., agents often acquire information about other agents that is not directly available to the principal (Fama and Jensen 1983). As a result, agents are also more likely than the principal to be aware of co-workers' opportunistic behavior. A survey of 725 executives and managers by Keenan (1988, 2000) indicates that 65 percent of the managers have personally observed or obtained direct evidence of one or more types of fraud, waste, or mismanagement within their companies. A 1998 survey by the Institute of Management and Administration reports that 45 percent of its respondents have observed other agents lying to their superiors (Darley et al. 2001, 55).

When an agent in a multidivisional firm reports his/her local information to the principal, his/her capacity to overstate local cost could be seriously undermined if there are other agents (either from the same division or from other divisions) who can observe his/her local information. Of course, this depends on the willingness of other agents to report the overstatement of cost to the principal.

Researchers have long noted the potential value of information that one agent possesses about another's activities (e.g., Fama and Jensen 1983; Kandel and Lazear 1992). The analytical modeling literature proposes a type of mutual monitoring system that can improve the principal's contractual position when the agents can perfectly or imperfectly observe each other. The common aspect of the system is that the principal encourages peer reporting and bases each agent's compensation on the peer's report (Demski and Sappington 1984; Demski et al. 1988; Ma 1988; Arya et al. 1996; Fischer and Hughes 1997). The agents are essentially whistleblowers, who pass on to the principal any information they gather about their co-workers (Towry 2003). The principal can extract private information at a lower cost when agent B reveals agent A's private information than when agent A reveals his own private information. In this paper, this type of system is referred to as a peer reporting system.

This study loosely focuses on a peer reporting system constructed by Ma (1988). Under Ma (1988), each agent observes the other agent's action and reports both his own action and his knowledge about the other agent's action to the principal. Each agent's compensation is based on the report filed by the other agent. The principal enforces the veracity of any negative peer report by requiring the accusing agent to accept an output-based lottery that is valuable only if the other agent did in fact lie.[3] An alternative way to verify the accusation, as suggested by Towry (2003), is for the firm to employ an auditor. The auditor is called only if one agent accuses the other of lying. The accusing agent is then rewarded (penalized) if the auditor determines that the accusation is truthful (false). If the agents are rational players, then they will always prefer to truthfully report their peer's action to the principal. By backward induction, the threat of peer reporting will deter agents from lying in the first place, and no audit will have to take place. Therefore, the system strictly improves the principal's welfare when compared with one that treats the agents independently.[4]

Introducing Peer Reporting to a Multi-Agent Budgeting Setting

Ma's (1988) model was originally used in a moral hazard situation. By logical extension, the model can also be applied to the information asymmetry case studied in this paper. The setting examined in this study is similar to Antle and Eppen's (1985) principal-agent model of the budgeting process, with the exception that the principal in this paper elicits information from two agents, A and B. Project completion requires the agents' presence, and funding is provided by the principal. The cost of project A is uniformly distributed as $c_A \in [c_{Amin}, c_{Amax}]$; the cost of project B is uniformly distributed as $c_B \in [c_{Bmin}, c_{Bmax}]$. The revenue of project A, R_A, is equal to c_{Amax}; the revenue of project B, R_B, is equal to c_{Bmax}. The firm's expected total surplus from the projects is given by $R_A - E(c_A) + R_B - E(c_B)$. The projects' revenue and the probability distribution over costs are both common knowledge. However, only the agents know both projects' actual costs. That is, the agents know their own actual cost and can perfectly observe the other's actual cost.

Under the assumption that both the principal and the agents have utility only for wealth, agent A and agent B will submit the highest feasible cost reports (i.e., c_{Amax} and c_{Bmax}, respectively) to the principal. Therefore, the agents appropriate the entire surplus from the projects.

To resolve the problem noted above, the principal can introduce a peer reporting system into the multi-agent budgeting setting. Assume that the principal utilizes the agents' knowledge about each other to enforce truthful reporting. Also, assume that the principal asks each agent to report his/her own cost, and then uses the other agent's reaction as a policing device. One agent's pay depends on the other agent's verification. Specifically, if agent B states that agent A honestly reported the cost of project A, then agent A receives his reservation utility payment, w , and will be reimbursed for the project cost he reported. If B states that A overstated the cost, then A will receive his reservation utility payment, w, and be fined f for overstating. Incentives to B's verification are provided by demanding that any accusation be supported by an audit. If B's accusation is proved to be right, then B is provided a bonus, b; if not, then B has to pay a penalty, p, for falsely accusing A.

---

[3] The peer reporting system used in this paper is the same as the vertical incentive system in Towry (2003), who used Ma's (1988) model. However, she modified Ma's (1988) model in two ways. First, Ma's (1988) model is asymmetric, i.e., agent A's task is to report both agents' actions and agent B's task is to verify agent A's reports. Towry (2003) took the spirit of that model and operationalized it with a symmetric model, i.e., both agents report their own actions and verify each other's report. Second, instead of using a lottery, Towry (2003) employed a costless auditor. While the lottery and the auditor have the same effect, the latter is both easier to understand and to operationalize in an experimental setting.

[4] A disadvantage of using an auditor as opposed to using a lottery to enforce truthful whistleblowing is that the principal would have to pay the auditor, making it a costly solution. However, if the agents are rational players, by backward induction, the threat of peer reporting will deter them from shirking in the first place. Therefore, in equilibrium, no whistleblowing will have to take place and the auditor is never called (Towry 2003). From the principal's perspective, this approach improves her welfare when compared with a simple one that treats the agents independently and audits every report from the agents.

The system involves a two-stage game. That is, each agent needs to make two sequential choices: either to honestly report or overstate his own cost in stage-one; and either to tell the principal that the other agent was honest or dishonest in stage-two. Given the system, an agent's expected payoff is determined by two factors: (1) how the other agent reports on him, and (2) how he reports on the other agent. Specifically, for any agent i $(i = \mathrm{A}, \mathrm{B})$. Depending on (1), agent i receives:

$w + (r_i - c_i)$, if agent $j (j = \mathrm{A,B}; j \neq i)$ reports agent i as *honest*;

$w + (r_i - c_i) - f = w - f$,[5] if agent j reports agent i as *dishonest*.

Depending on (2), agent i receives:

b, if agent i reports agent j as *dishonest* and the audit shows that j is *dishonest*;

$-p$, if agent i reports agent j as *dishonest* and the audit shows that j is *honest*; and

0, if agent i reports agent j as *honest*;

where:

w = reservation utility payment;
c_i = actual cost for division i;
r_i = resources provided to division i by the principal;
f = fine for overstating;
b = bonus for truthful accusation (whistleblowing), $(f \geq b > 0)$;[6] and
p = penalty for false accusation, $p > 0$.

In the current paper, the following specific parameters are used:

$w = 500$;

$$c_i = \begin{cases} c_A \in (c_{Amin}, c_{Amax}) \in (1000, 1050, \ldots, 2000, \ldots, 2950, 3000) \rightarrow E(c_A) = 2000; \\ c_B \in (c_{Bmin}, c_{Bmax}) \in (4000, 4050, \ldots, 5000, \ldots, 5950, 6000) \rightarrow E(c_B) = 5000; \end{cases}$$

$$r_i = \begin{cases} r_i = c_i & \text{if agent } j \text{ reports agent } i \text{ as dishonest;} \\ c_{imax} \geq r_i \geq c_i & \text{if agent } j \text{ reports agent } i \text{ as honest;} \end{cases}$$

---

[5] If agent j reports that agent i is dishonest, then an audit will take place and the resource transferred to division i, r_i, will be equal to the actual cost incurred, c_i.

[6] It is required that $f \geq b > 0$ because otherwise, agents will have incentive to overstate all the time and truthfully report their peers as dishonest to get the high reward for blowing the whistle.

$$E(r_i - c_i) = \begin{cases} 0 & \text{if agent } j \text{ reports agent } i \text{ as dishonest;} \\ 1000 & \text{if agent } j \text{ reports agent } i \text{ as honest;}^{7} \end{cases}$$

$f = 1000$;
$b = 1000$; and
$p = 2000$.

Given the above parameters, Table 1, Panel A summarizes the game in normal form. The game can be solved by backward induction, resulting in a unique subgame perfect Nash Equilibrium, in which each agent tells the truth both in stage-one and in stage-two. To demonstrate this, the agents play one of four subgames in making their whistleblowing decisions in stage-two depending on what the agents might have done in stage-one. For example, if agent A honestly reports his actual cost and agent B overstates in stage-one, then the stage-two subgame is represented by the four bottom left cells in Panel A of Table 1. By looking at the payoffs in the cells, regardless of what B does, A is always better off to tell the principal that B was dishonest. Regardless of what A does, B is always better off to tell the principal that A honestly reported the cost.[8] That is, the unique subgame perfect Nash Equilibrium for this subgame is for both A and B to truthfully tell the principal what the other party actually did in stage-one.

Knowing that the other agent will truthfully report on peers in stage-two, through backward induction, the agents are better off to honestly report their costs in stage-one.[9] The unique subgame perfect Nash Equilibrium for the game, and therefore the wealth-maximizing prediction for the game, is for both agents to honestly report their own cost in stage-one and truthfully tell the principal in stage-two that the other agent is honest. No whistleblowing or audit will have to take place. The peer reporting system thereby allows the principal to achieve the first-best outcome.

Fairness Perception and Honesty under the Peer Reporting System

A vital condition for a peer reporting system with a reward for whistleblowing is that wealth-maximizing agents will always pass along their knowledge about their peers to the principal, as long as the principal pays them their reservation utility wage. Whether the agents perceive their wage to be fair or unfair is irrelevant to their decisions. The analytical model treats whistleblowing on lying peers as given and does not probe into the processes through which this action is more or less likely to take place. In contrast, evidence from the whistleblowing literature shows that people are reluctant to blow the whistle on others despite the financial rewards. This literature further suggests that an agent's willingness to sanction a peer's misconduct by blowing the whistle depends on the agent's perception of the fairness of the principal (Miceli et al. 1991). This is because employee embezzlement and other similar acts are sometimes rationalized by fellow employees as being justified if employees feel that the employer is not being fair (Mars 1974; Greenberg 1987, 1990; Murphy 1992). Instead of stopping others from embezzling, employees

---

[7] Wealth-maximizing agent i should always overstate to c_{imax} if agent j does not report on him. In such a situation, $E(r_i - c_i) = c_{imax} - E(c_i) = 1000$.

[8] In the case when B tells the principal that A honestly reported the cost, if A blows the whistle on B, A will receive 1500 (500 wage + 1000 reward for whistleblowing) and B will receive −500 (500 wage − 1000 fine for overstating). If instead, A covers for B, A will receive 500 (wage) and B will receive 1500 (500 wage + 1000 slack).
In the case when B falsely accuses A to have overstated the cost, if A blows the whistle on B, A will receive 500 (500 wage − 1000 fine + 1000 reward), and B will receive −2500 (500 wage − 1000 fine − 2000 for false accusation). If A covers for B, A will receive −500 (500 wage − 1000 fine), B will receive −500 (500 wage + 1000 slack −2000 for false accusation). Therefore, in this subgame, no matter what B does, A is better off to blow the whistle on B. No matter what A does, B is better off not to falsely accuse A, that is, to tell the principal that A was honest in stage-one.

[9] Through backward induction, the stage-one game is to choose among the four stage-two subgame equilibria (the four shaded cells in Table 1, Panel A). By looking at the payoffs, regardless of what the other agent does in stage-one, an agent is always better off to honestly report his cost in stage-one.

TABLE 1

Agents' Expected Payoffs[a]

Panel A: Agents' Expected Payoffs When Wage = 500 Liras

		Agent B's Reporting Choices (Report Actual cost or Overstate) and Whistleblowing Choices (Report Agent A as Honest or Dishonest)			
Agent A's Reporting Choices (Report Actual cost or Overstate) and Whistleblowing Choices (report agent B as Honest or Dishonest)		**O, D**	**O, H**	**A, D**	**A, H**
	O, D	500, 500	2500, –500	–2500, 500	–500, –500
	O, H	–500, 2500	1500, 1500 collusive outcome	–500, 1500	1500, 500
	A, D	500, –2500	1500, –500	–2500, –2500	–1500, –500
	A, H	–500, –500	500, 1500	–500, –1500	500, 500*[b]

Panel B: Agents' Expected Payoffs When Wage = 1000 Liras

		Agent B's Reporting Choices (Report Actual cost or Overstate) and Whistleblowing Choices (Report Agent A as Honest or Dishonest)			
Agent A's Reporting Choices (Report Actual cost or Overstate) and Whistleblowing Choices (report agent B as Honest or Dishonest)		**O, D**	**O, H**	**A, D**	**A, H**
	O, D	1000, 1000	3000, 0	–2000, 1000	0, 0
	O, H	0, 3000	2000, 2000 collusive outcome	0, 2000	2000, 1000
	A, D	1000, –2000	2000, 0	–2000, 2000	–1000, 0
	A, H	0, 0	1000, 2000	0, –1000	1000, 1000*[b]

---

[a] Table 1 only shows payoffs calculated based on the expected actual costs. When actual costs are higher or lower than the expected costs, payoffs under some choice combinations can be higher or lower. However, the changes will not affect the result of the game. The unique subgame perfect Nash Equilibrium is still for both agents to honestly report their own costs in stage-one and to truthfully reveal their information about each other in stage-two.

[b] The two numbers in each cell represent the payoffs to agent A and agent B, respectively. The highlighted cells represent the unique Nash Equilibria of the four, stage-two subgames.

who feel exploited by the employer are more likely to conduct similar acts as a mechanism to correct perceptions of inequity (Hollinger and Clark 1983). These arguments lead to the following hypotheses:

H1a: *Ceteris paribus*, under a peer reporting system, agents report their costs more honestly when they perceive the principal as fair versus unfair.

H1b: *Ceteris paribus*, under a peer reporting system, the percentage of whistleblowing on lying peers is higher when they perceive the principal as fair versus unfair.

Communication and Collusion under the Peer Reporting System

Under the peer reporting system, there exists a collusive outcome (both agents lie to the principal in stage-one and cover for each other in stage-two) that benefits both agents but harms the principal.[10] Collusion between the agents poses a latent threat to the functioning of the peer reporting system.

A potentially important factor in determining collusion between the agents is the level of communication between them (Towry 2003). In practice, firms have differential arrangements and policies to encourage communication among employees. The level of collusion, as well as the effectiveness of the peer reporting system, can differ with variation of communication between the employees.

There are several competing hypotheses with regard to the effect of communication on honesty and collusion under the peer reporting system. Conventional economic theory suggests that, as long as employee communication is non-binding, the peer reporting system will be collusion-proof, regardless of the level of communication. This is because for collusion to occur, the collusive agreement between the agents must be self-enforcing, i.e., neither agent has an incentive to break the collusive agreement given that the other agent does not (Baiman et al. 1991; Harsanyi and Selten 1988). Under the peer reporting system (as in a typical Prisoner's Dilemma game), both agents have incentives to defect from the collusive agreement to receive the reward for whistleblowing. Therefore, communication between wealth-maximizing agents will not lead to dishonesty and collusion under the peer reporting system.

Alternatively, recent evidence from experimental cheap talk literature consistently suggests that non-binding communication can nonetheless increase the rate of cooperation in Prisoner's Dilemma Games (Radlow and Weidner 1966; Dawes et al. 1977; Dawes 1980; Farrell and Rabin 1996; Crawford 1998; Miller et al. 2002). This literature suggests that, in the current context, an increased level of communication will lead agents to collude with each other more frequently.

Finally, research in social psychology suggests that the effect of communication on employee collusion should be considered in a richer context. One feature that distinguishes the current study from prior experimental cheap talk studies is that the prior literature mainly involves a simple environment in which communication only affects the well being of the communicating players. The current study explores a more complex setting in which communication not only passes on a strategy that can mutually benefit the communicating players—the agents—but also conveys an intention that is harmful to a party who is not part of the communication—the principal. When the principal is in the game, whether the agents will exploit their collusion opportunity against the principal is affected by the agents' fairness perception of the principal.

When the principal is perceived as less fair, communication between the agents can reinforce the agents' feeling of unfairness, trigger their collusive intention, and allow them to explicitly coordinate on a collusive strategy. Folger and Kass (2000) suggest that peers' perceptions can be used as diagnostic information and that sharing work experiences with peers can mutually reinforce and change fairness perceptions. Lind et al. (1998) find that when participants are allowed to communicate and learn that they have shared mutual injustices, fairness ratings plummet. An employee who is surrounded by peers who complain that they are treated unjustly is more likely to interpret a supervisor's ambiguous behavior as unfair (Lind et al. 1998). This shared perception of unfairness will lead to a higher level of collusion between the parties who communicate.

---

[10] If the agents collude, then they can receive their wage plus the slack they build into the cost report. If they choose to be honest to the principal, they can only receive their wage.

H2a: When the principal is perceived as unfair, communication between the agents will decrease reporting honesty under the peer reporting system.

H2b: When the principal is perceived as unfair, communication between the agents will decrease the percentage of whistleblowing on lying peers under the peer reporting system.

In contrast, if the principal is perceived as fair, communication between the agents may not lead to increased collusion. On one hand, the agents should be more reluctant to use their communication ability to collude against a fair principal for two reasons. First, the agents may wish to reciprocate by being honest to a fair principal. Second, the agents may be afraid to hurt their social image by cheating a fair principal. Despite the fact that an agent might want to initiate a collusive offer, he might hesitate to do so, knowing that it violates social norms. Psychological research has shown that simply the suspicion that others disapprove of one's behavior when acting against the social norm can carry significant costs, such as feelings of shame or loss of self respect (Lindbeck 1997; Rege and Telle 2004). For this reason, one agent might hesitate to initiate a collusive offer to the other agent even if he personally would prefer to reap the benefit by colluding against the principal.

On the other hand, fairness perception may influence how a collusive suggestion is received by the other agent. When an agent sends a message suggesting colluding against a fair principal, this could undermine the sender's credibility because merely making this suggestion violates social norms. Therefore, the receiver of the message may reject the collusive offer because he believes that an agent who announces the willingness to collude against a fair principal cannot be trusted not to renege on this announcement if there is an economic advantage to reneging.

The discussion so far suggests that when the principal is perceived as fair, communication between the agents may not lead to increased collusion and reporting dishonesty. In fact, communication may even reduce the level of reporting dishonesty. This is because instead of using communication to form a collusive agreement, the agents may use it to reinforce the sense of positive reciprocity, that is, be honest to a fair boss (Folger and Kass 2000). The above arguments lead to the following research questions:

RQa: When the principal is perceived as fair, will communication between the agents decrease reporting honesty under the peer reporting system?

RQb: When the principal is perceived as fair, will communication between the agents decrease the percentage of whistleblowing on lying peers under the peer reporting system?

III. RESEARCH METHOD

A 2 × 2, Agent Communication (yes / no) × Wage (high/low) experiment was conducted with 60 participants recruited from undergraduate business classes from a large university. Two experimental sessions were conducted for each of the two communication conditions, with at least 12 participants in each session. As participants arrived, one-third were randomly selected to be the principals, the rest assumed the role of agents. Principals and agents were given instructions separately. After the instructions were explained, agents were further divided into two groups and were seated in rooms A and B. Each session consisted of eight periods. In each period, an agent A was matched with a new agent B and a new principal. No two agents were ever paired with each other more than twice, and no triads were ever repeated. Participants in the same room were never paired with each other, and they were not told who their partners were, either during or after the experiment.[11] Participants were informed that their final pay was determined by the result of one of the eight periods, which was randomly chosen. For each 1000 liras they earned that period, they received $15.

The agents were paid a wage (high, 1000 lira; or low, 500 lira) in each round. The agents' wage was designated by the principal matched with them in each round. This design is meant to manipulate the agents' fairness perception of the principal. The concept of fairness in this paper is based on the reciprocal fairness concept developed in the gift exchange literature. This literature suggests that, in judging the fairness of an action, people take into account the distributive consequences of an action as well as the intention that is signaled by the action (Rabin 1993; Fehr and Gächter 2000; Falk et al. 2000). When the principal has the option of choosing 500 liras or 1000 liras as the wage, a principal who chooses 1000 liras can be seen as giving a gift to the agents (since the principal reduces his/her own wealth by giving a higher wage when he/she does not have to). This action and the intention behind it should be perceived as fairer than the selection of the 500 lira wage. In addition, participants in this experiment were provided a benchmark for judging the fairness of the wage, i.e., they were informed that in the pilot study, the average wage chosen by the principals was 750 liras.[12]

The agents were responsible for reporting their production costs to the principal. Agent A's actual cost falls within (1000, 1050,…,2000,…,2950, 3000) liras, and agent B's cost falls within (4000, 4050,…,5000,…,5950, 6000) liras. Both agents knew their and the other agent's exact production cost. The principal, however, only knew the probability distribution of the possible production costs. The firm had a peer reporting system under which each agent was required to indicate whether his/her peer had overstated the cost after both agents independently reported their own costs. If any agent was accused of overstating, then he/she was fined 1000 liras. An audit took place, and the resources provided to the agent were equal to the actual production cost. If there was no accusation, then there was no audit, and the resources provided to the agent equaled the cost reported by the agent. If any agent blew the whistle on his/her peer, then the whistleblower received a 1000 lira reward if the result of the audit confirmed the accusation, but the whistleblower was fined 2000 liras if the audit revealed that the accusation was false.

---

[11] Participants were not repeatedly matched to avoid extraneous variables (such as reputation or "tit-for-tat" behaviors) as explanations for the agents' behaviors, as well as to better test Ma's model. Ma's model is for a one-shot game. If the participants were repeatedly matched with each other in the experiment, then they would have been involved in a multi-period game as opposed to eight one-shot games.

[12] A pilot study was run with 36 participants. The principals could choose from three wage levels (500, 750, 1000) in the pilot. Most principals chose 750 liras. The 750-lira wage was removed in this experiment in order to maximize the variance in wages. The 1000-lira wage was meant to proxy for fair wage, but may also be capturing the notion of generosity. However, on a relative basis, the post-experimental questionnaire clearly indicates that the 1000-lira wage was viewed as fairer than the 500-lira wage.

Table 1 presents the agents' expected payoffs when the principal pays them the 500 lira wage (Panel A) versus the 1000 lira wage (Panel B). As analyzed in Section II, no matter which wage they receive, wealth-maximizing agents should honestly report their costs to the principal and then tell the principal that their peer is honest. In equilibrium, the agents should both receive their wage, and only their wage.

Timeline in Each Experimental Period

Figure 1 shows the timeline in each period. In the no communication condition (hereafter, NCC), at the beginning of each experimental period, the principals were asked to choose the wage for the two agents matched with him/her in that period. The two agents in each triad received the same wage.

After learning their wage, the agents found out the actual costs for the two products and were asked to report their own production cost to the principal.[13] The experimenters then showed each agent the cost reported by his/her partner. Agents were then asked to circle whether their partners honestly reported or overstated. They were instructed that while they knew with certainty whether their partners overstated the cost, they could choose to circle either response, regardless of what their partners actually did. If an agent indicated that his/her partner overstated the cost, then the accussee was audited, and the payoffs were calculated. If an agent reported that his/her partner was honest, then there was no audit and the payoffs were calculated. Each participant was informed of his/her payoff for the period. The experiment consisted of eight periods. Participants completed a post-experimental questionnaire at the conclusion of the eighth period.

The timeline in the communication condition (hereafter CC) is the same as that in the NCC with one exception: the agents could communicate twice with each other after they learned their wage in each experimental period. Specifically, the two agents who were paired with each other for that period simultaneously wrote a message to each other. The messages were placed in envelopes and exchanged through the experimenters. After the agents read the message sent to them, they simultaneously wrote a response. The responses also were placed in envelopes and exchanged through the experimenters. The agents were told that they could write anything except for information that might reveal their personal identity. They were also told that writing was not obligatory. They did not have to write anything if they chose not to.

IV. RESULTS

Several manipulation check questions were used to ensure that participants understood the task and attended to the manipulations. With the exception of two agents in the NCC, all participants answered all check questions correctly. The two agents' data are excluded from the analyses. Overall, 20 agents in the NCC and 18 agents in the CC are included in the analyses.

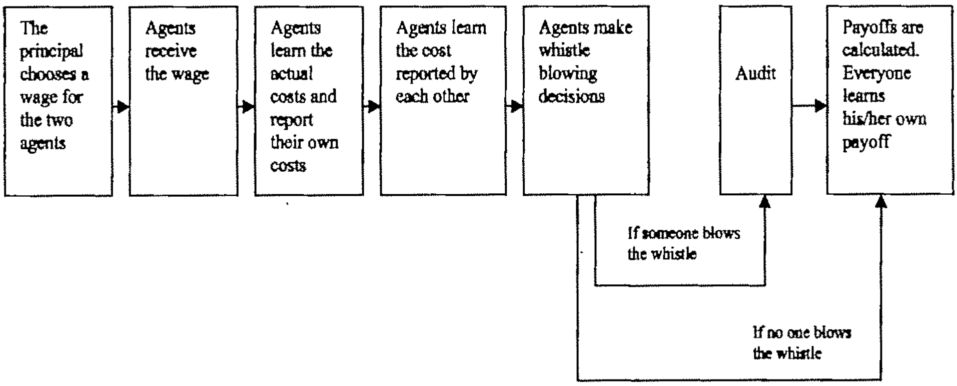
In the NCC, the agents received a total of 160 wage offers from the principals across the eight periods (20 agents × 8 periods), of which 92 (58 percent) were 500 lira offers and 68 (42 percent) were 1000 lira offers. In the CC, the agents received a total of 144 wage offers from the principals across the eight periods (18 agents × 8 periods), of which 118 (82 percent) were 500 lira offers and 26 (18 percent) were 1000 lira offers. The post-experimental questionnaire included a validity check on whether wage offers affected agents' fairness perception of the principal. Agents were

---

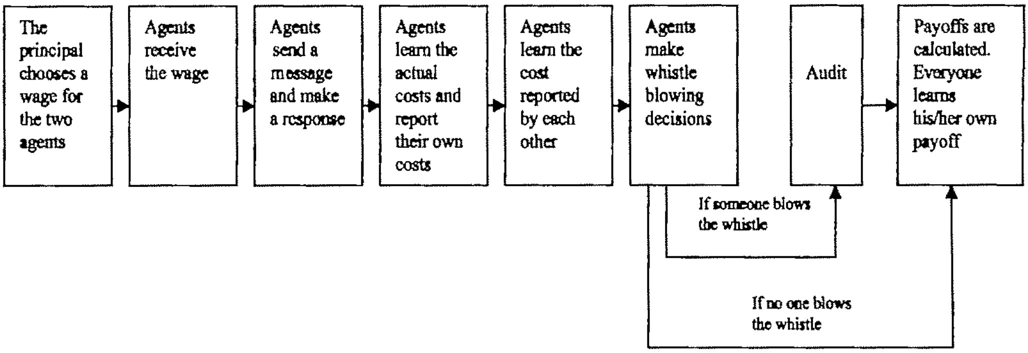
[13] To save time in the experiment, actual production costs for each period were predetermined by randomly drawing from 41 equally likely choices (1000, 1050,...,3000) for Division A and from 41 equally likely choices (4000, 4050,...,6000) for division B, with the exception of a few outliers (costs too close to the high or low end of the range) being thrown away. For any given period, the actual cost for all agent As are the same and the actual cost for all agent Bs are the same. The same set of costs was used in the two communication conditions.

FIGURE 1
Timeline in Each Experimental Period

NCC (No Communication Condition)


The principal chooses a wage for the two agents
Agents receive the wage
Agents learn the actual costs and report their own costs
Agents learn the cost reported by each other
Agents make whistle blowing decisions
Audit
Payoffs are calculated. Everyone learns his/her own payoff
If someone blows the whistle
If no one blows the whistle

CC (Communication Condition)


The principal chooses a wage for the two agents
Agents receive the wage
Agents send a message and make a response
Agents learn the actual costs and report their own costs
Agents learn the cost reported by each other
Agents make whistle blowing decisions
Audit
Payoffs are calculated. Everyone learns his/her own payoff
If someone blows the whistle
If no one blows the whistle

asked to rate, on a 1–7 point scale, how fair the principal was when s/he offered them a 500 (1000) lira wage (with 1 being the most unfair, 4 being neither fair nor unfair, and 7 being the most fair). Results show that receiving the 500 (1000) lira wage is highly correlated with agents' perception of the principal as unfair (fair). In the NCC, the mean fairness rating for the principal when he/she offered the 500 lira wage (2.3) is significantly lower than when he/she offered the 1000 lira wage (6.3) ($t = 12.92$, $p < 0.01$). In the CC, the mean fairness rating for the principal when he/she offered the 500 lira wage (2.2) is significantly lower than when he/she offered the 1000 lira wage

(5.7) ($t = 8.96$, $p < 0.01$). As a result, the wage offer (high or low) is used as a measure of the agents' fairness perception of the principal (high or low) in all analyses reported in this paper.[14]

The major dependent variables of this study are the agents' reporting honesty and the percentage of whistleblowing. An agent's reporting honesty refers to his/her honesty in reporting his/her own division's cost to the principal. Following Evans et al. (2001), reporting honesty is measured as "1 − Slack Claimed/Slack Available."[15] Similar to Towry (2003), the percentage of whistleblowing is defined as the percentage of truthful whistleblowing on lying peers.[16]

Table 2 contrasts wealth-maximizing predictions with major results from the current experiment. Panel A summarizes the wealth-maximizing predictions while Panel B reports the number of observations in each condition and the major results of the current experiment. Detailed analyses of participants' behaviors and tests of hypotheses are reported in the following sections.

The Agents' Reporting Honesty (H1a, H2a, and RQa)

Hypothesis 1a predicts that agents will report more honestly when they perceive the principal as fair versus unfair. I calculated, for each agent, the difference in average reporting honesty when wage was high versus when wage was low, and found that this measure is positive on average ($t = 3.08$, $p < 0.01$). Table 3 reports the agents' reporting honesty by wage and period. Wage significantly affected reporting honesty for six of the eight periods. Table 4 reports results of a linear mixed model test. The linear mixed model is used to test the effect of wage on the agents' reporting honesty while adjusting for correlation due to repeated observations on each participant over eight periods. Wage strongly affected agents' reporting honesty, supporting H1a ($F = 24.71$, $p < 0.01$). Further analyses on the simple effects of wage under each communication condition indicate that wage affected reporting honesty both in NCC ($F = 9.88$, $p < 0.01$) and in CC ($F = 12.25$, $p < 0.01$). This suggests that agents reacted strongly to social norm and overstated to a greater degree upon receiving a low wage, both when they could strategize with each other and when they could not.[17]

As a robustness test of H1a, I use the amount of slack in the agents' report as the dependent variable. The average slack was 337.62 liras when agents received the low wage and 81.91 liras when they received the high wage. A linear mixed model test suggests that wage significantly affected the amount of slack reported, both in NCC ($F = 15.16$, $p < 0.01$) and in CC ($F = 12.85$, $p < 0.01$), further supporting H1a.

Table 4 shows that communication also had a main effect on agents' reporting honesty ($F = 11.13$, $p < 0.01$). However, further analyses on the simple effects of communication under each wage condition suggest that communication had a significant effect on reporting honesty only when the wage was unfair. When the agents received the low wage, their mean reporting honesty in the NCC was 0.72, and their mean reporting honesty in the CC was 0.60 ($F = 3.85$, $p = 0.05$). This suggests that the agents' ability to communicate with each other significantly decreased the agents' reporting honesty when they received the low wage, supporting H2a. In contrast, communication did not affect reporting honesty when the wage was fair. When agents received the high

---

[14] I also analyzed the data using the agents' fairness ratings as the independent variable where appropriate. The results of such analyses are very similar to those reported in the paper.

[15] For example, if agent A's actual cost is 1400 liras, agent A's available slack by lying to the maximum extent (i.e., claiming 3000 liras as his/her cost) is 1600 liras. If agent A reported 2500 liras as the cost, then he/she claimed 1100 lira slack (=2500 − 1400) and his/her reporting honesty = 1 − 1100 / 1600 = 0.31.

[16] For example, if participant A_1 is matched with five overstating partners and A_1 only blows the whistle twice, then the percentage of whistleblowing for A_1 will be 40%.

[17] Arcsine square root transformation of reporting honesty was performed when reporting honesty was used as the dependent variable in linear models throughout this paper. This transformation is used to normalize the variable so that it is more suitable for linear tests.

TABLE 2
Wealth-Maximizing Predictions versus Results

Panel A: Wealth-Maximizing Predictions

	NCC		CC	
Wage	**Low Wage**	**High Wage**	**Low Wage**	**High Wage**
% of Wage Offers[a]	100%	0%	100%	0%
Reporting Honesty[b]	1.00	1.00	1.00	1.00
Number of Overstatements[c]	0	0	0	0
% of Whistleblowing[d]	NA	NA	NA	NA

Panel B: Experimental Results

	NCC		CC	
Wage (Fairness Rating)	**Low Wage (2.3)**	**High Wage (6.3)**	**Low Wage (2.2)**	**High Wage (5.7)**
% of Wage Offers	58% (= 92 / 160)	42% (= 68 / 160)	82% (= 118 / 144)	18% (= 26 / 144)
Reporting Honesty	0.72 (n = 92)	0.92 (n = 68)	0.60 (n = 118)	0.89 (n = 26)
Number of Overstatements	40	11	56	3
% of Whistleblowing	55% (= 22 / 40)	91% (= 10 / 11)	36% (= 20 / 56)	67% (= 2 / 3)
% of Collusive Agreements Formed	—	—	88% (= 52 / 59)	23% (= 3 / 13)

---

[a] (The number of x-lira wage offers)/(The total number of wage offers).

[b] 1 − Slack Claimed/Slack Available.

[c] The number of times the agents reported higher than their actual cost to the principals.

[d] The percentage of truthful whistleblowing on lying peers.

Hypotheses:

H1a: $(\text{Reporting Honesty})_{\text{low wage}} < (\text{Reporting Honesty})_{\text{high wage}}$

H1b: $(\%\text{ of Whistleblowing})_{\text{low wage}} < (\%\text{ of Whistleblowing})_{\text{high wage}}$

H2a: $(\text{Reporting Honesty})_{\text{CC-low wage}} < (\text{Reporting Honesty})_{\text{NCC-low wage}}$

H2b: $(\%\text{ of Whistleblowing})_{\text{CC-low wage}} < (\%\text{ of Whistleblowing})_{\text{NCC-low wage}}$

RQa: $(\text{Reporting Honesty})_{\text{CC-high wage}}$ versus $(\text{Reporting Honesty})_{\text{NCC-high wage}}$

RQb: $(\%\text{ of Whistleblowing})_{\text{CC-high wage}}$ versus $(\%\text{ of Whistleblowing})_{\text{NCC-high wage}}$

wage, their mean reporting honesty in the NCC was 0.92, and their mean reporting honesty in the CC was 0.89 ($F = 0.36$, $p = 0.56$). This result suggests an answer to RQa: When the agents received the high wage, their reporting honesty was high regardless of whether they could explicitly strategize their behaviors. Communication between them did not reduce reporting honesty. Using slack taken as the dependent variable confirms the above results. Communication between the

TABLE 3
Reporting Honesty by Wage and Period

Experimental Period	Low Wage	High Wage	p-value (one-tailed)
1	0.77 (n = 22)	0.98 (n = 16)	p = 0.01*
2	0.58 (n = 22)	0.77 (n = 16)	p = 0.11
3	0.56 (n = 24)	0.85 (n = 14)	p = 0.02*
4	0.69 (n = 29)	1.00 (n = 9)	p = 0.00**
5	0.68 (n = 27)	1.00 (n = 11)	p = 0.00**
6	0.58 (n = 30)	1.00 (n = 8)	p = 0.00**
7	0.57 (n = 28)	1.00 (n = 10)	p = 0.00**
8	0.77 (n = 28)	0.80 (n = 10)	p = 0.42
Total	0.65 (n = 210)	0.91 (n = 94)	

*, ** Significant at $p < 0.05$ and $p < 0.01$, respectively.

agents increased the amount of slack in the agents' reports when the wage was low ($F = 21.87$, $p < 0.01$). However, communication did not affect the amount of slack when the wage was high ($F = 0.11$, $p = 0.74$).

The Agents' Whistleblowing Behaviors (H1b, H2b, and RQb)

Hypothesis 1b predicts that the percentage of whistleblowing on peers' overstatements is higher when agents perceive the principal as fair versus unfair. When agents received the high wage, 14 overstatements were observed and agents blew the whistle on 12 of these overstatements (86 percent). Conversely, when agents received the low wage, 96 overstatements were observed and agents blew the whistle on 42 of these overstatements (44 percent). Since only a few agents overstated when they received the high wage, particularly in the CC, where agents only overstated three times, I ran a follow-up communication condition to increase the sample size for testing the agents' whistleblowing behaviors. In the follow-up condition, all 20 participants assumed the role of agents and the wage they received in each period followed the pattern of the wages received by participants in the NCC. Participants in the follow-up condition were asked to assume that they were working for a different company in each period and each company might choose to pay them a different wage. Three participants' data were eliminated from the analyses because they did not answer the check questions correctly. The remaining 17 participants received a total of 77 low wages and 59 high wages. After combining data from the follow-up condition with the original experiment, I selected agents ($n = 18$) who had overstating partners both when they received the high wage and when they received the low wage, and calculated two whistleblowing percentages

TABLE 4

Effects of Wage and Communication on Reporting Honesty[a]

Panel A: Main Effects

Source	F	p-value (two-tailed)
Communication	11.13	0.00
Wage	24.71	0.00
Wage * Communication	1.34	0.25

Panel B: Simple Effects

Source	F	p-value (two-tailed)
Effect of Wage under No Communication Condition (NCC)	9.88	0.00
Effect of Wage under Communication Condition (CC)	12.25	0.00
Effect of Communication under Low Wage Condition	3.85	0.05
Effect of Communication under High Wage Condition	0.36	0.56

---

[a] Dependent variable: arcsine square root transformation of reporting honesty.
Reporting honesty for each agent is equal to (1 − Slack Claimed/Slack Available).

(one for the low wage condition and one for the high wage condition) for each of them. I then ran a repeated-measure ANOVA to test the effect of wage and communication on the whistleblowing percentages. As reported in Table 5, wage only marginally increased the whistleblowing percentage ($F = 2.31$, $p = 0.07$, one-tailed). Further analyses on the simple effects suggest that wage increased whistleblowing when agents could communicate with each other ($F = 4.25$, $p = 0.04$, one-tailed). When the agents could not communicate with each other, wage did not increase whistleblowing ($F = 0.05$, $p = 0.42$, one-tailed).

Hypothesis 2b predicts that communication between agents will decrease whistleblowing when they receive the low wage. RQb asks whether communication will decrease whistleblowing when agents receive the high wage. As shown in Table 5, communication decreased whistleblowing when the wage was unfair ($F = 4.21$, $p = 0.04$, one-tailed), consistent with H2b. When the wage was high, communication did not have significant effects on agents' whistleblowing behaviors ($F = 0.16$, $p = 0.69$, two-tailed). This suggests an answer to RQb: Communication between agents does not decrease whistleblowing when agents receive the high wage from the principal.

The Agents' Colluding Behaviors in the CC

Explicit communication between agents allows them to strategize their actions. A more detailed look at the CC suggests that wage also affected agents' strategic behaviors, i.e., the number of collusive agreements they formed with their partner. A message was coded as collusive if it

TABLE 5

Effects of Wage and Communication on Individual Whistleblowing Percentage[a]

Panel A: Main Effects

Source	dof	F	p-value (two-tailed)
Wage	1	2.31	0.15
Communication	1	2.85	0.11
Wage * Communication	1	1.44	0.25
Error	16		

Panel B: Simple Effects

Source	dof	F	p-value (two-tailed)
Effect of Wage under No Communication Condition (NCC)	1	0.05	0.84
Effect of Wage under Communication Condition (CC)	1	4.25	0.07
Effect of Communication under Low Wage Condition	1	4.21	0.07
Effect of Communication under High Wage Condition	1	0.16	0.69

[a] Two whistleblowing percentages are calculated for each agent who had overstating peers both when they received the high wage and the low wage. The denominator of the percentage for the low (high) wage condition is the number of times an agent had a peer that overstated the cost when he/she received the low (high) wage. The numerator is the number of times the agent blew the whistle in that situation.

expressed an intention to overstate the cost and/or to cover for each other.[18] A final collusive agreement was formed if both agents sent a collusive message to each other in their second round of communication. Results show that, of the 59 agent pairs who received the low wage, 52 pairs (88 percent) formed a final collusive agreement. In contrast, only three out of the 13 agent pairs (23 percent) who received the high wage formed a final collusive agreement. The difference is statistically significant ($\chi^2 = 25$, $p < 0.01$).[19]

I address whether the agents' collusive behaviors mediated the effect of wage on agents' reporting honesty. I conducted a regression analyses on reporting honesty with wage and a "collusive agreement" dummy (yes or no) as the explanatory variables. Results indicate that forming a collusive agreement has a negative effect on reporting honesty ($t = -1.95$, $p < 0.03$, one-tailed).

---

[18] For example, the message "Overstate to the max and no ratting" was coded as collusive; while the message "I get paid more this time. My wage is a lot. Let's be honest" was coded as non-collusive. Blank messages were also coded as non-collusive. The messages were independently coded by the author and two doctoral students. The results were compared and there is unanimous agreement among the coders.

[19] Results in the follow-up communication condition confirm that fairness affects agents' collusive behaviors. A Chi-square test shows that agent pairs who received the low wage offer formed significantly more final collusive agreements with each other than those who received the high wage ($\chi^2 = 36.7$, $p < 0.01$).

More importantly, the effect of wage on reporting honesty just barely reaches the threshold for significance ($t = 1.38$, $p = 0.09$, one-tailed) after including the collusive agreement dummy in the model.[20] These results suggest that, when opportunities to collude with other agents are present, the effect of perceived fairness on agents' reporting honesty is mediated, at least partially, by the collusive agreement formed between them.

The Principal's Payoff and Wage Choices

This section briefly summarizes how fairness and communication affect the principal's gross margin. In this experiment, the sales revenue of product A (B) is 3000 liras (6000 liras). The gross margin equals the sales revenue on the products minus the resources provided to the two agents. If an agent is honest, then the resources provided to him/her equal the actual cost of the product. If an agent overstates the cost, then resources provided to the agent equal the overstated cost if the other agent covers for him/her, and equal the actual cost if the other agent blows the whistle. In other words, the gross margin is jointly determined by the agents' reporting honesty and the extent of whistleblowing on any dishonest report. As detailed in Table 6, the gross margin is significantly associated with wage ($F = 9.91$, $p < 0.01$), with the effect being significant in CC ($F = 5.15$, $p = 0.03$) and in NCC ($F = 4.63$, $p = 0.04$). Results show that offering the high wage in CC increased the gross margin by 465 liras. Agent communication decreased gross margin when the wage was low ($F = 4.45$, $p = 0.04$), but not when the wage was high ($F = 0.31$, $p = 0.58$). From

TABLE 6

The Principal's Gross Margin

Panel A: Main Effects

Source	**dof**	**F**	**p-value (two-tailed)**
Wage	1	9.91	0.00
Communication	1	2.33	0.13
Wage * Communication	1	0.96	0.33
Error	140		

Panel B: Simple Effects

Source	**dof**	**F**	**p-value (two-tailed)**
Effect of Wage under No Communication Condition	1	4.63	0.04
Effect of Wage under Communication Condition	1	5.15	0.03
Effect of Communication under Low Wage Condition	1	4.45	0.04
Effect of Communication under High Wage Condition	1	0.31	0.58

---

[20] Results in the follow-up communication condition are similar. Forming a collusive agreement has a negative effect on reporting honesty ($t = -2.63$, $p < 0.01$, one-tailed) and the effect of wage on reporting honesty is nonsignificant ($t = 0.93$, $p = 0.18$, one-tailed).

the principal's perspective, paying the high wage is profitable only if the return from the higher gross margin is greater than the cost of higher wages. The principal in the current study earned more when they offered the low wage since the increase in gross margin did not cover the price of appearing fair.[21] Nevertheless, the principals offered a significant number of high wages to the agents. A Mann-Whitney test suggests that the principals sent significantly more high wage offers in the NCC than in the CC ($p = 0.02$, one-tailed). The principals' responses in the post-experimental questionnaire suggest that the principals in the CC were concerned that communication might lead the agents to collude against them, and they were reluctant to offer the 1000-lira wage to the agents when this possibility exists. Results were consistent with the notion that the principals had a preference for fairness in their wage choices, particularly in the NCC, where the principals feel less likely to be exploited by the agents.[22]

V. CONCLUSION

Control systems relying on peer monitoring are frequently observed in practice and represent a potentially cost effective way to improve the principal's contractual position. This study investigates behaviors under a peer reporting system in a controlled experiment. The results suggest the following: first, inconsistent with the wealth-maximizing assumption, agents did not always report honestly under the peer reporting system. They reported less honestly when they received the low wage than when they received the high wage. The wage level was highly related to agents' perceived fairness of the principal. Second, communication between agents further decreased their reporting honesty when they received the low wage, but not when they received the high wage. Additional analyses suggest that in the communication condition, agents formed more collusive agreements with each other when they received the low wage than when they received the high wage, and collusive agreements mediated the effect of wage on reporting honesty. Third, in a controlled experiment where there was virtually no reputation cost or the possibility of retaliation, many agents did not blow the whistle on their peers despite the high reward for doing so. The whistleblowing percentage is significantly lower ($t = 2.67$, $p = 0.01$) in the low wage, communication condition than in other conditions. Finally, the owners did not always choose the low wage, despite the fact that they may profit more when doing so.

This study contributes to the management accounting literature in several ways. First, evidence is provided that two factors, the agents' perceived fairness of the principal and inter-agent communication, play important roles in determining agents' behaviors under a peer reporting system with a whistleblowing function. As such, this study adds to the growing evidence that incentive systems are affected by factors outside conventional agency theory and suggests that these factors need to be considered in incentive contracting design.

Second, this study demonstrates how the dynamics within a one-principal, two-agent setting, affect agents' mutual monitoring and colluding behaviors in the context of a peer reporting system. By doing so, this study suggests the importance for experimental research to examine accounting issues in multi-person settings, and answers the call for accounting research to examine multi-person issues across various incentive systems, production environments, and communication and monitoring arrangements (Fisher 1994; Sprinkle 2003).

---

[21] Readers should keep in mind that several elements of this study are biased in favor of principals who offered the low wage. Such elements include the substantial difference between the high and low wages, the limit on the scope of cost overstatement, and the fact that the audit on whistleblowing is costless. Thus, the conclusion that the principals are better off when offering the low wage should be interpreted with caution.

[22] One explanation for the owners' wage choices is suggested by Evans et al. (1994). In their study, the owner experiences disutility from the possibility of being exploited by the managers to whom the owner has entrusted his/her assets. The owners in Evans et al. (1994) are willing to pay to avoid the possibility of being exploited.

Third, this paper has implications for management in practice. Results of this paper suggest that, for organizations that established a peer reporting system, the important benefit of increasing agents' fairness perception is not so much about encouraging agents' whistleblowing, but rather about reducing the need to blow the whistle by reducing the likelihood that agents would engage in opportunistic behaviors. In addition, this study has implications to modern organizations that adopt costly policies and activities to encourage communication among employees. Specifically, results suggest that agent communication can lead to collusion and other counter-productive activities when agents perceive unfairness in the organization.

Certain limitations of this study should be noted. This study makes a simplifying assumption that agents can perfectly observe each other's local information, whereas in practice, agents may only be able to imperfectly observe each other. As a result, there can be doubts about whether other agents have in fact built-in slack in their reports. Additionally, some levels of slack can be desirable to the organization and may not necessarily be dishonest.[23] These uncertainties can increase the ambiguity of a peer's behavior. As a result, the deterrent effect of peer reporting may not be as strong in practice as those found in this study. Future research in this area may want to investigate these issues.

Another noticeable limitation is that the current study is single-period in nature. A single-period experiment serves the purpose of providing a clean test of factors of interest and benchmarking against the economic theory. However, it lacks external validity because it excludes many real-world influences, such as reputation and strategy formation, which may arise from long-term relationships and repeated interactions. Nevertheless, there are reasons to believe that extending this study to a multi-period experiment with repeated interaction may lead to stronger fairness effects. This is because long-term relationships and repeated interaction can strengthen social ties between agents, which in turn can increase their level of collusion if they believe that the principal is treating them unfairly. Future studies may want to explore this issue further. One final note is that principals in this experiment are not allowed to communicate with agents, nor can they choose whether they want to adopt the peer reporting system. It will be interesting to investigate whether giving principals more choices and allowing them to interact more with agents can affect the agents' fairness perceptions and honesty level. These extensions suggest fruitful areas for future research.

REFERENCES

Antle, R., and G. Eppen. 1985. Capital rationing and organizational slack in capital budgeting. *Management Science* 31 (2): 163–174.

Arya, A., J. Glover, and R. A. Young. 1996. Capital budgeting in a multidivisional firm. *Journal of Accounting, Auditing & Finance* 11 (4): 519–533.

Baiman, S., J. H. Evans, and N. Nagarajan. 1991. Collusion in auditing. *Journal of Accounting Research* 29 (1): 1–18.

Crawford, V. 1998. A survey of experiments on communication via cheap talk. *Journal of Economic Theory* 78: 286–298.

Darley, J. M., D. M. Messick, and T. R. Tyler. 2001. *Social Influences on Ethical Behavior in Organizations*. Mahwah, NJ: Lawrence Erlbaum Associates.

---

[23] In my setting, slack represents expropriation of rents by agents—if agents overstate their costs, then it indicates with certainty that they do so for opportunistic reasons. In practice, slack can be beneficial to the organization by reducing agent tension, increasing organizational resiliency to change, protecting the organization against uncertainty in the environment, and by making available some resources that can be used for innovation (Sprinkle 2003; Merchant 1998).

Dawes, R. M., J. McTavish, and H. Shaklee. 1977. Behavior, communication and assumptions about other people's behavior in a commons dilemma situation. *Journal of Personality and Social Psychology* 35 (1): 1–11.

———. 1980. Social dilemma. *Annual Review of Psychology* 31: 169–193.

Demski, J. S., and D. Sappington. 1984. Optimal incentive contracts with multiple agents. *Journal of Economic Theory* 33: 152–171.

———, ———, and P. T. Spiller. 1988. Incentive schemes with multiple agents and bankruptcy constraints. *Journal of Economic Theory* 44: 156–167.

Evans, J. H., V. Hoffman, and S. Rau. 1994. The accountability demand for information. *Journal of Management Accounting Research* 6: 24–42.

———, L. Hannan, R. Krishnan, and D. V. Moser. 2001. Honesty in agential reporting. *The Accounting Review* 76 (4): 537–559.

———, and D. V. Moser. 2004. Agency theory and incentive contracting experiments. Working paper, University of Pittsburgh, Pittsburgh, PA.

Falk, A., E. Fehr, and U. Fischbacher. 2000. Testing theories of fairness—Intentions matter. Working Paper No. 63, University of Zurich.

Fama, E. F., and M. C. Jensen. 1983. Separation of principal subjectship and control. *The Journal of Law & Economics* 26 (2): 301–325.

Farrell, J., and M. Rabin. 1996. Cheap talk. *The Journal of Economic Perspectives* 10 (3): 103–118.

Fehr, E., and S. Gächter. 2000. Fairness and retaliation: the economics of reciprocity. *The Journal of Economic Perspectives* 14 (3): 159–181.

Fischer, P. E., and J. S. Hughes. 1997. Mutual monitoring and best agency contracts. *Journal of Institutional and Theoretical Economics* 153: 334–355.

Fisher, J. G. 1994. Technological interdependence, labor production functions and control systems. *Accounting, Organizations and Society* 19: 493–505.

———, L. Maines, S. Peffer, and G. Sprinkle. 2002. Using budgets for performance evaluation: Effects of resource allocation and horizontal information asymmetry on budget proposals, budget slack, and performance. *The Accounting Review* 77 (4): 847–865.

Folger, R., and E. E. Kass. 2000. Social comparison and fairness: A counterfactual simulations perspective. In *Handbook of Social Comparison: Theory and Research*, edited by J. Suls, and L. Wheeler. New York, NY: Kluwer Academic/Plenum Publishers.

Greenberg, J. 1987. A taxonomy of organizational justice theories. *Academy of Management Review* 12: 9–22.

———. 1990. Employee theft as a reaction to underpayment inequity: The hidden cost of pay cuts. *The Journal of Applied Psychology* 75 (5): 561–568.

Hannan, R. L. 2005. The combined effect of wage and firm profit on employee effort. *The Accounting Review* 80 (1): 167–188.

Harsanyi, J. C., and R. Selten. 1988. *A General Theory of Equilibrium Selection in Games*. Cambridge, MA: MIT Press.

Hollinger, R., and J. Clark. 1983. *Theft by Employees*. Lexington, MA: Lexington Books.

Kandel, E., and E. Lazear. 1992. Peer pressure and partnerships. *The Journal of Political Economy* 100 (4): 801–817.

Keenan, J. P. 1988. Communication climate, whistleblowing and the first level agent: A preliminary study. *Academy of Management Best Paper Proceedings* 40: 247–251.

———. 2000. Blowing the whistles on less serious forms of fraud. *Employee Responsibilities and Rights Journal* 12 (4): 199–217.

Lind, E. A., L. Kray, and L. Thompson. 1998. The social construction of injustice: Fairness judgments in response to own and others' unfair treatment by authorities. *Organizational Behavior and Human Decision Processes* 75 (1): 1–22.

Lindbeck, A. 1997. Incentives and social norms in household behavior. *The American Economic Review* 87 (2): 370–377.

Luft, J. L. 1997. Fairness, ethics and the effect of management accounting on transaction costs. *Journal of Management Accounting Research* 9: 199–216.

Ma, C. 1988. Unique implementation of incentive contracts with many agents. *The Review of Economic Studies* 55 (4): 555–572.

Mars, G. 1974. Dock pilferage: A case study in occupational theft. In *Deviance and Social Control*, edited by P. Rock, and M. McIntosh. London, U.K.: Tavistock Institute.

Merchant, K. A. 1998. *Modern Management Control Systems*. Upper Saddle River, NJ: Prentice Hall.

Miceli, M. P., J. P. Near, and C. R. Schwenk. 1991. Who blows the whistle and why? *Industrial & Labor Relations Review* 45 (1): 113–130.

Miller, J. H., C. T. Butts, and D. Rode. 2002. Communication and cooperation. *Journal of Economic Behavior & Organization* 47: 179–195.

Murphy, K. R. 1992. *Honesty in the Workplace*. Monterey, CA: Brooks/Cole Publishing Company.

Rabin, M. 1993. Incorporating fairness into game theory and economics. *The American Economic Review* LXXXIII: 1281–1302.

Radlow, R., and M. F. Weidner. 1966. Unenforced commitments in cooperative and non-cooperative non-constant-sum games. *Journal of Conflict Resolution* 10 (4): 497–505.

Rankin, F., S. Schwartz, and R. Young. 2003. Management control using non-binding budgetary announcements. *Journal of Management Accounting Research* 15: 75–93.

Rege, M., and K. Telle. 2004. The impact of social approval and framing on cooperation in public good situations. *Journal of Public Economics* 88 (7–8): 1625–1644.

Sprinkle, G. B. 2003. Perspectives on experimental research in agential accounting. *Accounting, Organizations and Society* 28 (2–3): 287–318.

Towry, K. 2003. Control in a teamwork environment—The impact of social ties on the effectiveness of mutual monitoring contracts. *The Accounting Review* 78 (4): 1069–1095.

THE ACCOUNTING REVIEW
Vol. 83, No. 4
2008
pp. 1147–1152

American Accounting Association
DOI: 10.2308/accr.2008.83.4.1147

BOOK REVIEW

Stephen A. Zeff, Editor

Editor's note: Two copies of books for review should be sent to the Book Review Editor: Stephen A. Zeff, Rice University, Jesse H. Jones Graduate School of Management, 6100 Main St., Houston, TX 77005. The policy of *The Accounting Review* is to publish only those reviews solicited by the Book Review Editor. Unsolicited reviews will not be accepted.

CHRISTOPHER S. CHAPMAN, ANTHONY G. HOPWOOD, and MICHAEL D. SHIELDS, *Handbook of Management Accounting Research* (Oxford, U.K.: Elsevier, 2007, ISBN 13: 978-0-08-045340-8, pp. xi, xiii, 1204).

The editors of this handbook, which consists of two 600-page hardcover volumes, have aspired to provide an overview of the current state of systematic knowledge in the field of management accounting and in the research processes that develop this knowledge (p. ix). There is every reason for the editors to undertake this work: management accounting ideas and techniques have been mainly developed in practice, responding to different and changing needs and following diverse developments in time and space. This is also reflected in our body of knowledge: management accounting theory is inspired by various theoretical orientations, it has produced a diverse and loosely coupled set of ideas and systems, using a large variety of research methodologies. Some may see this as a strength: management accounting theory seems to reflect the diversity in practice. Others argue that it has caused management accounting to be a fragmented and unstructured academic discipline, rendering the process of knowledge creation and accumulation ineffective and inefficient. Here is where the book contributes most: it gives a fairly complete and well-structured overview of our current academic knowledge in management accounting. The editors managed to secure 42 high-quality papers from 73 internationally respected academics, and they have organized them in such a way that the book as a whole provides a reasonably well-balanced overview of the historical advancements and current knowledge in management accounting. Almost all of the contributions were especially written for the handbook, only three are revised versions of earlier publications (i.e., Chapters 2 and 6 in Volume 1, and Chapter 6 in Volume 2), and one is a thoroughly revised and updated version of an earlier paper (Chapter 12 in Volume 2). The book should be read by young researchers because it helps them become oriented in theoretical approaches and practical topics, as well as how they can be studied. It will also help advanced researchers rethink their current approach and discover new avenues for future work. In this way, the handbook provides a service to the research community by making the knowledge creation and dissemination process more effective and efficient.

The handbook is unique for its unprecedented scope. We have had survey books before, but they all had their limitations. For example, Bhimani's book, *Management Accounting* (Bhimani 1996), is restricted to the European region, Hopper et al.'s book, *Issues in Management*

Accounting (Hopper et al. 2007), takes a more instructional approach on subjects relevant to practice, while other books focus on specific topics, like *Management Accounting in the Digital Economy* (Bhimani 2003) and *Management Accounting for Performance Measurement and Control* (Epstein and Manzoni 2002). The editors structured the handbook according to six perspectives: (a) the scope of management accounting research literature, (b) theoretical perspectives, (c) research methods, (d) management accounting topics (which the editors labeled "practices"), (e) management accounting in different organizational settings (labeled as "practices in context"), and (f) management accounting in different countries and regions (entitled "management accounting around the world").

The first three sections (comprising Volume 1) focus primarily on the theoretical orientations and research methods of academic work in management accounting, whereas the last three sections (Volume 2) provide an overview and discussion of management accounting research in specific subjects, organizational settings, and in geographical regions. The content of each section, as well as its boundaries, is not always clearly defined. A good example is the first section, which seems to be designed as an introduction. The first article by Hesford, Lee, Van der Stede, and Young is especially interesting for its overview of topics, methods, journals, and research networks. They conclude that researchers have shifted attention from budgeting and organizational control topics to performance measurement and evaluation topics during the last 20 years. Given this result, it is surprising to see that this handbook does address budgeting and organizational control, but it offers no specific chapters on performance measurement. Hesford et al. identify, based on citation and social network analyses, several subnetworks of management accounting scholars. Notable is the existence of two distinct networks: one favoring control topics, analytical research, and economics-based theoretical orientations, whereas the other focusing more on sociological aspects of management accounting and its role in organizations. The first is more centered around eight North American journals, and the second is more related to Australian and European journals.

The second chapter by Luft and Shields shows how different management accounting papers structure their research models, but I think the strength of this paper is more methodological and therefore would have been better placed in the research methods section of the book. What is missing in the first section, however, is a chapter explaining what the structure of the book is and how the chapters relate to each other.

The second section on theoretical perspectives illustrates the large variety of theoretical orientations in our literature. Ahrens and Chapman show in the first chapter of this section that accounting cannot be understood by reference to its functional properties; instead, it has to be understood in its broader organizational context. Some theoretical interpretations, like governmentality, actor network theory, new notions of accountability, and situated functionality are introduced, and some of them reappear frequently throughout the remainder of the book. This chapter is followed by chapters on other basic disciplines and their role in management accounting research, such as psychology (Birnberg, Luft, and Shields), economics (Bromwich), contingency theory (Chenhall), critical theory (Cooper and Hopper), agency theory (Lambert), history (Luft), and sociology (Miller). Especially worthwhile reading is the psychology chapter, in which a distinction has been made between the psychological effects of management accounting practices (as, for instance, target setting and risk distribution) on motivation, and the cognitive processes of perceiving and processing management accounting information.

In the economics chapter, Bromwich explains the economic foundations of accounting-related topics, like costing, cost analysis, transfer pricing, capital budgeting, decision making, and control (agency theory). Most of the advancements in these areas have been developed in relative isolation, and Bromwich calls for more "tourism" across areas and more collaboration between economics and other theoretical orientations. I think it is worthwhile repeating his message here.

Chenhall provides an extensive review of contingency theoretical research in management control, looking at contextual and organizational variables. His critical evaluations of research outcomes in each area identify many new research opportunities. I expect most readers to be familiar with contingency theory and to recognize many topics in Chenhall's overview. Many fewer readers will be acquainted with critical theory, at least I am not. Cooper and Hopper did a good job opening up this area by connecting critical thinking to specific topics, like strategic management accounting and new public management. However, sometimes this textual material has made it difficult for me to understand the full meaning of certain explanations. For instance: "there are studies of how accounting logic or what Power et al. (2003) call 'accountingisation' has colonised what Habermas terms the 'life world'" (p. 226). The single quotation marks indicate that the terms have a specific meaning, and I am afraid that I do not fully comprehend them and appreciate their implications.

Lambert's chapter on agency theory is not placed adjacent to Bromwich's contribution, with which it combines nicely. (The chapters seem to be presented according to the alphabetical ordering of the first authors' names, which I find curious.) The great point of Lambert's contribution is that it shows that management and financial accounting have much more in common than we are inclined to believe: performance measures' informativeness, the design of optimal contracts, earnings management, and investment decisions are problems relevant to internal management as well as to investors. Much of our knowledge is based on descriptions and interpretations of management accounting practices.

Luft looks at historical theorizing and shows that management accounting practices need to be interpreted within their economic and social context for a better understanding. This chapter can best be read in combination with chapters on critical theory and on doing qualitative research.

Miller's chapter is particularly worthwhile reading, because it provides an overview of the most influential sociological approaches, better enabling the reader to comprehend the literature discussed in other chapters. For this reason, I would have positioned this chapter as the first in this section.

The research methods section contains eight contributions: qualitative field research (Ahrens and Chapman), quantitative field research (Anderson and Widener), comparative research (Bhimani), analytic modeling (Demski), interventionist research (Jönsson and Lukka), archival research (Moers), experimental research (Sprinkle and Williamson), and survey research (Van der Stede, Young, and Chen). This section portrays the large variety of research methods applied in our field, while each chapter also convincingly shows the significant contribution which each research method has made to the management accounting literature. Some chapters cover research methods that can be found in most books on research methodology, but two stand out in this regard. Bhimani's comparative research chapter and Jönsson and Lukka's interventionist research (perhaps better known as "action research") are surprising and especially interesting additions.

In their opening chapter, Ahrens and Chapman position qualitative field research as an alternative to positivism, which sees the empirical reality as objective and external to the subject. Qualitative field researchers see social reality to be emergent, subjectively created, and objectified through human interaction. Researchers should be open and sensitive to different interpretations of social reality, and they should not be guided by strict methodological rules, because these rules are at best indirectly helpful and potentially counterproductive. Although I follow the authors' reasoning at this point, the chapter leaves me behind with an unsatisfied feeling about *how* we can help future researchers to undertake good qualitative field research that makes their studies "plausible" and "trustworthy." To this end, a good addition to the handbook might be a chapter on case research methods, explaining how to structure the data collection process (such as interviews), how to interpret their contents (see, for, instance the discussions in the Appendix in Brownell

[1995]), and how to report transparently about the research (and the potential role of computer-aided qualitative data analysis systems).

Anderson and Widener show how the use of quantitative data, and especially the construction and measurement of latent variables, can add to the quality of field studies. They show how researchers may use multiple measures from multiple sources to reach a more complete, reliable, and insightful understanding of reality. Jönsson and Lukka take this story even further and discuss the consequences of becoming deeply immersed in the object of study, being involved in local action, recording developments as they unfold, and learning from change processes. The active posture of the researcher opens up new opportunities to collect more subtle and significant data, but introduces new complications, like the limited controllability over the research agenda, making theoretical sense of the pragmatism in finding the "right" solutions, and interpreting *ex post* the decision situation correctly.

The final chapter by Van der Stede, Young, and Chen on survey research not only discusses the difficulties in conducting survey research, like survey construction, defining level of analysis and sample size, and checking nonresponse bias and measurement reliability, but it also advocates new ways of dealing with these difficulties, other than uncritically duplicating the survey procedures employed in earlier studies.

The handbook's second volume begins with a section on management accounting practices, addressing specific management accounting topics that have surfaced in the research literature. It contains a selection of 13 papers: strategic cost management (Anderson), target costing (Ansari, Bell, and Okano), cost and profit driver research (Banker and Johnston), analytical cost modeling (Christensen and Hemmer), fiscal compliance with transfer pricing (Cools and Emmanuel), budgeting (Covaleski, Evans, Luft, and Shields), information technology (Dechow, Granlund, and Mouritsen), activity-based costing (Gosselin), economics of transfer pricing (Göx and Schiller), capital budgeting (Haka), operations management (Hansen and Mouritsen), management control and strategy (Langfield-Smith), and control and accountability (Merchant and Otley).

Anderson's contribution begins with a review of the strategic cost management literature, and she discusses interorganizational cooperative relations later on in the chapter. I admire the way she integrated both themes in one chapter, but I think both topics merit separate chapters. The topic of interorganizational management accounting is covered by Håkansson and Lind, but this contribution is placed in another section and therefore is not visible as an important topic. Each chapter provides a brief explanation of the topic and an extensive review of the research literature, mostly followed by suggestions for future work. The literature reviews may help readers to orient themselves in our field and to make well-informed decisions where they want to contribute. These reviews, however, are also very much a product of their time and may become outdated quickly, as new research is published. I personally favor Hansen and Mouritsen's contribution, because they convincingly demonstrate how intimately the decisions on decentralization, technology development, measurement systems, standard setting, and performance evaluation are related to each other.

A section like this cannot be expected to cover all developments in management accounting fully, yet I think the editors and authors did a wonderful job in covering at least the most important topics. However, I would have liked to see a chapter on performance measurement and evaluation (like balanced scorecards and value-based management systems) that discusses the antecedents of the selection of financial and nonfinancial measures, causality issues in performance models, the impact of performance information on decision making, and performance effects of measurement choices.

The last two sections view management accounting practices in different contexts: section five looks at different organizational and industry settings, whereas the final section focuses on management accounting practices in different national and regional environments. Section five is relatively short. It presents management accounting research in health care (behavioral studies are covered by Abernethy, Chua, Grafton, and Mahama; and economics-based studies are treated by Eldenburg and Krishnan), in the manufacturing sector (Davila and Wouters), and in interorganizational settings (Håkansson and Lind).

Abernethy et al. show how much the development of management accounting in health care is dependent on other institutional, political, and organizational factors. This chapter even helped me understand the critical perspectives paper better (Chapter 7 in Volume 1). Davila and Wouters' chapter on the manufacturing industry is a good example of how an approach of combining different theoretical orientations and research approaches can lead to a coherent and insightful image of management accounting in its empirical context. In my view, a similar piece of work could also have produced an equally interesting paper on the service sector, and perhaps also on small- and medium-sized enterprises and on multinational companies. In general, the governmental and non-profit sector is not widely represented in this handbook. This section would have been an ideal place to correct this imbalance by discussing management accounting issues in state and local governmental institutions, and in other independent non-profit organizations.

The final section, entitled "Management Accounting Around the World," discusses management accounting in different geographical regions. All contributions describe the historical developments and current distinctive features of the management accounting body of knowledge and its application in a specific country or region. It presents views from southern Europe (more specifically France, Italy, Portugal, and Spain, written by Carmona), the People's Republic of China (Chow, Duh, and Xiao), Britain (Boyns and Edwards), German-speaking countries (i.e., Germany, Austria, and part of Switzerland, by Ewert and Wagenhofer), the United States (Fleischman and Tyson), the Nordic countries (i.e., Sweden, Denmark, Norway, Finland, and Iceland, by Näsi and Rohde), and Japan (Okano and Suzuki). This section shows how influential the institutional developments are for the development and use of management accounting ideas. At the same time, the totality of these papers shows how management accounting knowledge began traveling at an increasing pace across regions from the mid-20th century onward. I personally favor the chapters about countries that have not yet been widely published in the English language, like German-speaking countries, China, and Japan. Each of these chapters presents new and exciting information, and therefore merit our special attention.

REFERENCES

Bhimani, A., ed. 1996. *Management Accounting, European Perspectives.* Oxford, U.K.: Oxford University Press.

——, ed. 2003. *Management and Accounting in the Digital Economy.* Oxford, U.K.: Oxford University Press.

Brownell, P. 1995. *Coopers & Lybrand Accounting Research Methodology Monograph No. 2.* Research Methods in Management Accounting. Melbourne, Australia: Coopers & Lybrand Australia.

Epstein, M. J., and J.-F. Manzoni, eds. 2002. *Studies in Managerial and Financial Accounting. Kidlington.* In *Performance Measurement and Management Control: A Compendium of Research,* Vol. 12 edited by M. J. Epstein. Oxford, U.K.: Elsevier.

Hopper, T., D. Northcott, and R. Scapens, eds. 2007. *Issues in Management Accounting.* 3rd edition. Harlow, U.K.: Pearson Education.

TOM GROOT
Professor of Management Accounting
VU University, Amsterdam

Editorial Data

The following table contains information about turnaround time for manuscripts (including revisions) on which editorial decisions were made in the 12-month period ended May 31, 2007. Turnaround time is the number of days between the date that the manuscript was received *and the date of the editor's letter to the author(s).*

	Number of Manuscripts	Percent	Cumulative Number	Cumulative Percent
0 ≤ Days ≤ 30	39	8.32	39	8.32
31 ≤ Days ≤ 60	153	32.62	192	40.94
61 ≤ Days ≤ 90	153	32.62	345	73.56
91 ≤ Days ≤ 120	86	18.34	431	91.90
121 ≤ Days	38	8.10	469	100.00
Total	469	100.00		

The mean review time was 70; the median review time was 66 days.

New Submissions by calendar year (January 1 to December 31)

1992	241
1993	234
1994	231
1995	195
1996	230
1997	195
1998	196
1999	239
2000	260
2001	260*
2002	324
2003	327
2004	307
2005	389
2006	413
2007	443

*2001—in addition to the 260 regular submissions, 68 MSs were submitted to the *TAR* Quality of Earnings Conference.

The acceptance rate (defined as number of MSs accepted divided by the number of new submissions) over the past 5 years is between 12–16% per year.

EDITORIAL POLICY AND STYLE INFORMATION

EDITORIAL POLICY

According to the policies set by the Publications Committee (which were endorsed by the Executive Committee and were published in the *Accounting Education News*, June 1987), *The Accounting Review* "should be viewed as the premier journal for publishing articles reporting the results of accounting research and explaining and illustrating related research methodology. The scope of acceptable articles should embrace any research methodology and any accounting-related subject, as long as the articles meet the standards established for publication in the journal ... No special sections should be necessary. The primary, but not exclusive, audience should be—as it is now—academicians, graduate students, and others interested in accounting research."

The primary criterion for publication in *The Accounting Review* is the significance of the contribution an article makes to the literature. Topical areas of interest to the journal include accounting information systems, auditing and assurance services, financial accounting, management accounting, taxation, and all other areas of accounting, broadly defined. The journal is also open to all rigorous research methods.

The efficiency and effectiveness of the editorial review process is critically dependent upon the actions of both authors submitting papers and the reviewers. Authors accept the responsibility of preparing research papers at a level suitable for evaluation by independent reviewers. Such preparation, therefore, should include subjecting the manuscript to critique by colleagues and others and revising it accordingly prior to submission. The review process is not to be used as a means of obtaining feedback at early stages of developing the research.

Reviewers and editors are responsible for providing constructive and prompt evaluations of submitted research papers based on the significance of their contribution and on the rigor of analysis and presentation.

MANUSCRIPT PREPARATION AND STYLE

The Accounting Review's manuscript preparation guidelines follow *The Chicago Manual of Style* (15th ed.; University of Chicago Press). Another helpful guide to usage and style is *The Elements of Style*, by William Strunk, Jr., and E. B. White (Macmillan). Spelling follows *Webster"s Collegiate Dictionary.*

FORMAT

1. All manuscripts should be formatted in 12-point font on 8 1/2 x 11" paper and should be double-spaced, except for indented quotations.
2. Manuscripts should be as concise as the subject and research method permit, generally not to exceed 7,000 words.
3. Margins should be at least one inch from top, bottom, and sides.
4. To promote anonymous review, authors should not identify themselves directly or indirectly in their papers or in experimental test instruments included with the submission. Single authors should not use the editorial "we".
5. A cover page should show the title of the paper, all authors' names, titles and affiliations, email addresses, and any acknowledgments.

Pagination: All pages, including tables, appendices and references, should be serially numbered. Major sections should be numbered in Roman numerals. Subsections should not be numbered.

Numbers: Spell out numbers from one to ten, except when used in tables and lists, and when used with mathematical, statistical, scientific, or technical units and quantities, such as distances, weights and measures. For example: *three days; 3 kilometers; 30 years.* All other numbers are expressed numerically.

Percentages and Decimal Fractions: In nontechnical copy use the word percent in the text.

Hyphens: Use a hyphen to join unit modifiers or to clarify usage. For example: *a cross-sectional equation; re-form.* See *Webster's* for correct usage.

Keywords: The abstract must be followed by at least three keywords to assist in indexing the paper and identifying qualified reviewers.

Data availability: A line immediately following the Keyword identifiers should indicate whether the data are available (see "Data Availability" later in this statement).

ABSTRACT/INTRODUCTION

An Abstract of about 100 words (150 maximum) should be presented on a separate page immediately preceeding the text. The Abstract should concisely inform the reader of the manuscript's topic, its methods, and its findings. Keywords and the Data Availability statements should follow the Abstract. The text of the paper should start with a section labeled "I. Introduction," which provides more details about the paper's purpose, motivation, methodology, and findings. Both the Abstract and the Introduction should be relatively nontechnical, yet clear enough for an informed reader to understand the manuscript's contribution. The manuscript's title, but neither the author's name nor other identification designations, should appear on the Abstract page.

TABLES AND FIGURES

The author should note the following general requirements:

1. Each table and figure (graphic) should appear on a separate page and should be placed at the end of the text. Each should bear an Arabic number and a complete title indicating the exact contents of the table or figure. Tables and figures should define each variable. The titles and definitions should be sufficiently detailed to enable the reader to interpret the tables and figures without reference to the text.
2. A reference to each graphic should be made in the text.
3. The author should indicate where each graphic should be inserted in the text.
4. Graphics should be reasonably interpreted without reference to the text.
5. Source lines and notes should be included as necessary.

Equations: Equations should be numbered in parentheses flush with the right-hand margin.

DOCUMENTATION

Citations: Within-text citations are made using an author-year format. Cited works must correspond to the list of works listed in the "References" section. Authors should make an effort to include the relevant page numbers in the within-text citations.

1. In the text, works are cited as follows: author's last name and year, without comma, in parentheses. For example: one author, (Berry 2003); two authors, (Fehr and Schmidt 2003); three or more authors, (Dechow et al. 1998); more than one work cited, (Cole and Yakushiji 1984; Dechow et al. 1995; Levitt 1998); with two works by the same author(s), (Nelson 2003, 2005).
2. Unless confusion would result, do not use "p." or pp." before page numbers. For example, (Dechow and Dichev 2002, 41–42).
3. For cited works that include more than one work by an author (or same co-authors) that are published in the same year, the suffix a, b, etc., is to follow the date in the within-text citations and in the "References" section. For example: (Baiman and Rajan 2002a, 2002b).
4. When the author's name is mentioned in the text, it need not be repeated in the citation. For example: "Cohen et al. (2005) provide ..."
5. Citations to institutional works should use acronyms or short titles where practicable. For example: (NCFFR, The Treadway Commission 1987).
6. If the paper refers to statutes, legal treatises, or court cases, citations acceptable in law reviews should be used.

Reference List: Every manuscript must include a "References" section that contains only those works cited within the text. Each entry should contain all information necessary for unambiguous identification of the published work. Use the following formats (which follow *The Chicago Manual of Style*):

1. Arrange citations in *alphabetical order* according to the surname of the first author or the name of the institution or body responsible for the published work.
2. Arrange citations in *chronological order* when two or more works are by the same first author (regardless of co-authors). Two or more works by the *same author(s)* published in the same year are distinguished by letters a, b, etc., after the year.
3. Use authors' initials instead of proper names.

4. For two or more authors, separate authors with a comma, including a comma before "and" (Dechow, P. M., R. Sloan, and A. Sweeney).
5. Date of publication follows the author's (authors') name(s).
6. Titles of journals or newspapers should not be abbreviated.

Sample entries are as follows:

Baiman, S., and M. Rajan. 2002a. The role of information and opportunism in the choice of buyer-supplier relationships. *Journal of Accounting Research* 40 (2): 247–278.

———, and ———. 2002b. Incentive issues in inter-firm relationships. *Accounting, Organizations and Society* 27 (3): 213–238.

Berry, R. 2003. Testimony before the Senate Committee on Homeland Security and Governmental Affairs Permanent Subcommittee on Investigations. November 18. Available at: http://hsgac.senate.gov/files/111803berry.pdf.

Cohen, D., A. Dey, and T. Lys. 2005. The Sarbanes Oxley Act of 2002: Implications for compensation structure and risk-taking incentives of CEOs. Working paper, New York University, University of Chicago, and Northwestern University.

Cole, R., and T. Yakushiji, eds. 1984. *The American and Japanese Auto Industries in Transition.* Ann Arbor, MI: University of Michigan.

Dechow, P. M., R. Sloan, and A. Sweeney. 1995. Detecting earnings management. *The Accounting Review* 70 (2): 193–225.

———, S. P. Kothari, and R. L. Watts. 1998. The relation between earnings and cash flows. *Journal of Accounting and Economics* 25: 133–168.

———, and I. Dichev. 2002. The quality of accruals and earnings: The role of accrual estimation errors, *The Accounting Review* 77 (Supplement): 35–59.

Easton, P. 2003. Discussion of: The predictive value of expenses excluded from pro forma earnings. *Review of Accounting Studies* 8: 175–183.

Engel, E., R. Hayes, and X. Wang. 2007. The Sarbanes-Oxley Act and firms' going-private decisions. *Journal of Accounting and Economics* (forthcoming).

Financial Accounting Standards Board (FASB). 2006. *Accounting for Uncertainty in Income Taxes, and Interpretation of FASB Statement No. 109.* FASB Interpretation No. 48. Financial Accounting Series. Norwalk, CT: FASB.

Fehr, E., and K. Schmidt. 2003. A theory of fairness, competition, and cooperation. In *Advances in Behavioral Economics,* edited by C. Camerer, G. Loewenstein, and M. Rabin, 271–296. New York, NY: Princeton University Press.

Janis, I. L. 1982. *Groupthink: Psychological Studies of Policy Decisions and Fiascoes.* Boston, MA: Houghton Mifflin.

Levitt, A. 1998. The numbers game. Speech delivered at New York University, Center for Law and Business, September 28.

Maggi, G. 1999. The value of commitment with imperfect observability and private information. *RAND Journal of Economics* (Winter) 30: 555–574.

National Commission on Fraudulent Reporting (the Treadway Commission). 1987. *Report of the National Commission on Fraudulent Financial Reporting.* Washington, D.C.: NCFFR.

Nelson, M. W. 2003. Behavioral evidence on the effects of principles- and rules-based standards. *Accounting Horizons* 17 (1): 91–104.

———. 2005. A review of experimental and archival conflicts-of-interest research in auditing. In *Conflicts of Interest: Challenges and Solutions in Business, Law, Medicine, and Public Policy,* edited by D. A. Moore, D. M. Cain, G. Loewenstein, and M. H. Bazerman. Cambridge, U.K.: Cambridge University Press.

Rigdon, E. E., R. E. Schumacker, and W. Wothke. 1998. A comparative review of interaction and nonlinear modeling. In *Interaction and Nonlinear Effects in Structural Equation Modeling,* edited by R. E. Schumacker, and G. A. Marcoulides, 1–16. Mahwah, NJ: Erlbaum Associates.

Schultz, E., and T. Francis. 2002. Companies profit on workers' deaths through "dead peasants" insurance. *Wall Street Journal* (April 19): 1.

Securities and Exchange Commission (SEC). 2002. *Certification of Disclosure in Companies' Quarterly and Annual Reports.* Release Nos. 33-8124, 34-46427. Washington, D.C.: SEC.

U.S. House of Representatives. 2002. The Sarbanes-Oxley Act of 2002. Public Law 107-204 [H. R. 3763]. Washington, D.C.: Government Printing Office.

Footnotes: Footnotes are not used for documentation. Textual footnotes should be used only for extensions and useful excursions of information that if included in the body of the text might disrupt its continuity. Footnotes should be inserted using the "footnote" or "endnote" feature of the word processing software which will automatically number the footnotes throughout the manuscript with superscript Arabic numerals.

SUBMISSION OF MANUSCRIPTS

Authors should note the following guidelines for submitting manuscripts:

1. Manuscripts currently under consideration by another journal or publisher should not be submitted. The author must state upon submission that the work is not submitted or published elsewhere.
2. For manuscripts reporting on field surveys or experiments: If the additional documentation (e.g., questionnaire, case, interview schedule) is sent as a separate file, then all information that might identify the author(s) must be deleted from the instrument.
3. Manuscripts should be submitted via email as Microsoft Word or PDF file to the Senior Editor, Steven Kachelmeier, at email address tar@mccombs.utexas.edu. Please submit separate files for (1) the manuscript's title page with identifying information (not forwarded to reviewers), (2) the manuscript with title page and all other identifying information removed, and (3) any necessary supplemental files, such as experimental instructions and/or response memoranda on invited revisions. The body or subject line of the email should also indicate the submission fee receipt code from AAA (see step 4 below).
4. A submission fee is required unless explicitly waived by the editor for invited revisions of previous submissions. The submission fee should be paid online (VISA or MasterCard only) at: https://aaahq.org/AAAforms/journals/tarsubmit.cfm. If unable to pay online, a check in U.S. funds, made payable to the American Accounting Association, may be sent to Ms. Mary Capps, Editorial Assistant, *The Accounting Review*, The University of Texas at Austin, McCombs School of Business, Department of Accounting CBA 4M.202, 1 University Station B6400, Austin, TX 78712-0211. The submission fee in U.S. funds is $125.00 for members and $200.00 for nonmembers of the AAA. The submission fee is nonrefundable.
5. Revisions must be submitted within 12 months from the decision letter inviting a revision.

COMMENTS

The Accounting Review welcomes submissions of comments on previous *TAR* articles. Comments on articles previously published in *The Accounting Review* will generally be reviewed by two reviewers, usually including an author of the original article (to assist the editor in evaluating whether the submitted comment represents the prior article accurately) and an additional reviewer who is independent of the original article. If a comment is accepted for publication, the original author will generally be invited to reply. All other editorial requirements, as enumerated above, apply to proposed comments.

POLICY ON REPRODUCTION

An objective of *The Accounting Review* is to promote the wide dissemination of the results of systematic scholarly inquiries into the broad field of accounting.

Permission is hereby granted to reproduce any of the contents of the *Review* for use in courses of instruction, as long as the source and American Accounting Association copyright are indicated in any such reproductions.

Written application must be made to the American Accounting Association, 5717 Bessie Drive, Sarasota, FL 34233-2399, for permission to reproduce any of the contents of the *Review* for use in other than courses of instruction—e.g., inclusion in books of readings or in any other publications intended for general distribution. In consideration for the grant of permission by the *Review* in such instances, the applicant must notify the author(s) in writing of the intended use to be made of each reproduction. Normally, the Review will not assess a charge for the waiver of copyright.

Except where otherwise noted in articles, the copyright interest has been transferred to the American Accounting Association. Where the author(s) has (have) not transferred the copyright to the Association, applicants must seek permission to reproduce (for all purposes) directly from the author(s).

POLICY ON DATA AVAILABILITY

The following policy was adopted by the Executive Committee in its 1989 meeting. "An objective of (*The Accounting Review, Accounting Horizons, Issues in Accounting Education*) is to provide the widest possible dissemination of knowledge based on systematic scholarly inquiries into accounting as a field of professional research, and educational activity. As part of this process, authors are encouraged to make their data available for use by others in extending or replicating results reported in their articles. Authors of articles which report data dependent results should footnote the status of data availability and, when pertinent, this should be accompanied by information on how the data may be obtained."

JULY 2008 PLACEMENT ADS

The deadline for information to be included in the "Placement Information" section is two months prior to the date of publication. The ***Review*** *is published in January, March, May, July, September, and November. Placement advertising and replies should be sent to the American Accounting Association, 5717 Bessie Drive, Sarasota, FL 34233-2399, ATTENTION: ADVERTISING DEPT. All replies to box numbers should be on separate sheets to facilitate forwarding.*

401 SOUTHERN ILLINOIS UNIVERSITY EDWARDSVILLE invites applications for a tenure-track position beginning in August 2009. A Ph.D. in Accounting is required, but ABDs nearing completion will be considered. Candidates must be qualified to teach financial accounting and must be committed to excellence in teaching and scholarly research. The Department of Accounting offers AACSB-accredited programs at both the undergraduate and master's levels. SIUE is located on a suburban campus of 2700 acres approximately 25 minutes from downtown St. Louis, MO. Send *vita* to: Michael L. Costigan, Chair, Department of Accounting, Campus Box 1104, Southern Illinois University Edwardsville, Edwardsville, IL 62026-1104; Email: mcostig@siue.edu. SIUE is a state university—benefits under state sponsored plans will not be available to holders of F1 or J1 visas. SIUE is an Equal Opportunity/Affirmative Action Employer, and applications from women and minorities are especially encouraged.

402 EMPORIA STATE UNIVERSITY Department of Accounting and Information Systems seeks a Visiting Professor of Accounting for Spring Semester/January 2009. A Ph.D. in Accounting from an AACSB-accredited school is required. ABDs will be considered. University teaching experience in financial accounting, particularly accounting theory and consolidations, is desired with documentation evidencing a high level of classroom effectiveness required. Review of applications will begin immediately. Send a letter of application addressing the position requirements, *curriculum vitae*, and the names, addresses, and telephone numbers of at least three references to: Dr. James F. Waegelein, Chair, Department of Accounting and Information Systems, Emporia State University, 1200 Commercial, Campus Box 4057, Emporia, KS 66801-5087. For more information call: (620) 341-5346; Fax: (620) 341-6346; Email: ACIS@emporia.edu. Emporia State University encourages minorities and women to apply. AA/EOE institution.

403 WINTHROP UNIVERSITY is seeking an Assistant/Associate Professor of Accounting. Duties include: Teach accounting courses for undergraduate accounting majors, undergraduate and graduate business students, and as part of the University general education program; conduct research in field of specialization; provide service to the business community; and other activities that support the mission of the College of Business Administration. Ph.D. is required for tenure-track appointment or ABD near completion in accounting. ABDs considered for non-tenure-track Instructor appointment. The area of specialization is open. Candidate must demonstrate effectiveness as a teacher and possess an acceptable record of research. For details on position visit: cba.winthrop.edu/administration/employment/default.htm. Review begins May 1, 2008. Direct questions to: Dr. Clarence Coleman, Search Chair; Phone: (803) 323-2678; Email: colemanc@winthrop.edu. EOE.

404 UNIVERSITY OF DELAWARE Alfred Lerner College of Business and Economics invites applications for two tenure-track faculty positions: Assistant Professor in Financial/Managerial Accounting (#3796); Assistant Professor in Taxation (#3797) beginning September 2009. Primary qualifications include outstanding research potential and teaching ability, doctorate in Accounting or be ABD. Candidates are expected to teach undergraduate- and graduate-level courses. Salary, benefits, and support are competitive with AACSB-accredited schools. Will interview with applicants at 2008 American Accounting Association meeting in Anaheim, CA. Send names of three references, *cv*, and summaries of teaching performance by September 15, 2008 to: Search Committee, Accounting and MIS, University of Delaware, Newark, DE 19716; Email: warrenn@lerner.udel.edu. Indicate the position number/title in your application. Application materials will be shared with department faculty. The University of Delaware is an Equal Opportunity Employer and encourages applications from minority group members and women.

405 UNIVERSITY OF OKLAHOMA Michael F. Price College of Business, the Steed School of Accounting seeks a full-time, renewable term Assistant Professor. The position is available for August 2008. The initial appointment is for two years. Salary and health-care benefits are competitive. Job Description: The primary duties include teaching, mentoring students, and serving as a division emissary to various college events. Instruction may involve both undergraduate and graduate (M.B.A.) courses. The teaching load is six–seven courses a year and may involve multiple preparations. Job Qualifications: A Ph.D. in Accounting. The ideal candidate will have excellent teaching capabilities, teaching experience, and a willingness to teach a variety of accounting courses as needed. Application Procedure: Please send a letter of application containing a clear statement of specific teaching interests, a resume, evidence of teaching capabilities, and the names of three references to: Dr. Frances L. Ayres, Director of Steed School of Accounting, Michael F. Price College of Business, Adams Hall, ST 200, University of Oklahoma, Norman, OK 73019. Screening for the position will begin April 14, 2008 and will continue until the position is filled. For further information, please contact Dr. Ayres: Email: fayres@ou.edu; Phone: (405) 325-4223. The University of Oklahoma is committed to Affirmative Action, Equal Opportunity and the diversity of its workforce.

406 FAYETTEVILLE STATE UNIVERSITY Job Title: Assistant Professor, Department of Accounting, Position Number: 6088-1101-0001-414. Job duties: Each faculty member is expected to teach 12 semester hours (9 if teaching an M.B.A. course), engage in scholarly and professional activities, and participate in student advisement and university services. This position is subject to the successful completion of an employment background check. An employment background check includes a criminal background check, employment verification, reference checks, license verification (if applicable), and credit history check (if applicable). Minimum Education and Experience: The candidate must have earned a Ph.D. degree in Accounting; CPA, CMA, or CIA preferred. ABDs in their final dissertation stage will be considered. Candidates for the rank of Associate Professor must show evidence of scholarly and professional activities. Knowledge, Skills, and Abilities: Ph.D. in Accounting with demonstrated ability to teach courses in the following areas: Financial, Managerial and Cost Accounting, Accounting Systems, Advance Accounting, Auditing, and M.B.A. courses. Salary: Commensurate with education and experience. Special instructions for applicants: Apply via website: https://jobs.fsu.edu. In addition, please submit three letters of recommendation with original signatures, official transcripts from colleges/universities listed on application, current *vitae*, and three work related references to: Ulysses Taylor, Fayetteville State University, School of Business and Economics, Rm 382 SBE, Fayetteville, NC 28301.

407 LOYOLA MARYMOUNT UNIVERSITY Department of Accounting invites applicants for two full-time tenure-track faculty positions at Assistant/Associate rank, effective Fall 2008. A doctorate (or short-term ABD status) in Accounting from an AACSB-accredited university is required. All candidates should demonstrate a strong commitment to scholarly research and excellence in teaching. All areas of accounting teaching will be considered. Salary is competitive and research support is available. If you are interested in learning more about these positions, contact: Professor Mahmoud Nourayi, Department of Accounting, College of Business Administration, Loyola Marymount University, One LMU Drive, Los Angeles, CA 90045-2659. Loyola Marymount, a comprehensive university in the mainstream of American Catholic higher education, seeks professionally outstanding applicants who value its mission and share its commitment to academic excellence, the education of the whole person, and the building of a just society. Visit http://www.lmu.edu for more information. LMU is an Equal Opportunity institution actively working to promote an intercultural learning community. Women and minorities are encouraged to apply.

408 SOUTHEASTERN OKLAHOMA STATE UNIVERSITY Department of Accounting and Finance in the John Massey School of Business invites applications for a tenure-track Assistant or Associate Professor of Accounting. Founded in 1909, Southeastern Oklahoma State University enrolls approximately 4,000 students in 41 undergraduate and 9 graduate degree programs. The John Massey School of Business completes its year of record in the AACSB accreditation process AY 2007-2008. The successful candidate for the position will possess the following qualifications: A master's degree, and a CPA or 18 graduate hours in accounting. A Ph.D. or ABD in Accounting preferred. Qualified candidates should submit a letter of application, *curriculum vitae*, unofficial transcripts, and names, addresses, phone numbers, and email addresses (if available) of at least three references to: Chair, Accounting Search Committee, c/o Dean, John Massey School of Business, Southeastern Oklahoma State University, School of Business, PMB 4128, Durant, OK 74701-0609. Review of applications will begin immediately and continue until the position is filled. Candidate must be eligible to work in the United States. Visit: http://www.se.edu. SE is an AA/EEO employer committed to multicultural diversity.

409 MICHIGAN TECHNOLOGICAL UNIVERSITY invites applicants for a tenure-track Assistant/Associate/Full Professor in Accounting starting August 2009. This position requires a Ph.D. in Accounting from an AACSB-accredited institution. The successful candidate will be expected to develop a vigorous, nationally visible research program as well as contribute effectively to both undergraduate and graduate instruction. The School of Business and Economics (http://www.sbe.mtu.edu) is AACSB-accredited, offers competitive salaries, attractive benefits, and a reduced teaching load and summer start-up funding for junior faculty. Interested candidates should send a letter of application, resume, evidence of scholarly activity, evidence of teaching effectiveness, and three references to: School of Business and Economics at: sbe-search@mtu.edu. Michigan Tech (http://www.mtu.edu), is a nationally recognized research university and a leader in science and engineering education. Located in the scenic Upper Midwest, Michigan Tech offers a friendly, safe, and affordable living environment with excellent opportunities for year-round outdoor recreation.

410 ALFRED UNIVERSITY AACSB-accredited College of Business invites applications for a tenure-track position at the Assistant Professor level in accounting, beginning in the Fall 2009. The position requires a Ph.D. in Accounting (ABD considered if evidence of completion within one year), D.B.A. with research interests in Accounting, or equivalent degree in Accounting. Professional certification preferred. The teaching load will include graduate/undergraduate levels in one or more areas including financial or managerial accounting. Applications will be considered as of September 1, 2008. Review of applications will continue until the position is filled. To apply please send a letter of application, *vita*, evidence of teaching capabilities (if available) and at least three recommendation letters to: Accounting Search Committee, College of Business, Alfred University, Saxon Drive, Alfred, NY 14802; or Email: businesscollege@alfred.edu Alfred University is an AA/EOE employer.

411 UTAH STATE UNIVERSITY School of Accountancy in the Jon M. Huntsman School of Business offers a nine-month (academic year) tenure-track position at the rank of Assistant, Associate, or Full Professor in Accounting beginning August 2008 (or until filled). The role requires approximately 70 percent teaching, 20 percent research, and 10 percent service and professional engagement activities. The department has outreach programs within the Utah State University system. As part of USU's mission to make its academic programs accessible throughout the state, this position will be physically located at the USU–Tooele Regional Campus in Tooele, Utah. See: http://jobs.usu.edu (Req. ID 051282) for full job description and to apply online. AA/EOE

412 BRYANT UNIVERSITY Department of Accounting, invites applications for a full-time tenure-track position beginning August 1, 2009. Rank is at the Assistant Professor level. Bryant University is a private AACSB-accredited university with undergraduate and master's degree programs in accounting. Quality teaching and research productivity are expected of faculty members. The salary is competitive and will be based upon qualifications. Candidates must be either: (1) ABD or (2) have completed a doctorate or equivalent from a nationally recognized accounting program accredited by AACSB International. Preference will be given to candidates able to teach courses in Managerial Accounting and/or Auditing. The selected candidate will be expected to be an active member of the department and academic community. Complete information regarding the required application process is available online at: http://employment.bryant.edu. To receive full consideration, interested persons must apply electronically. The review of applications will begin immediately and the position will remain open until filled. Bryant University faculty members will be conducting interviews at the 2008 American Accounting Association Annual Meeting in Anaheim. Bryant is an EEO/AA Employer and an institution committed to diversifying its faculty.

413 TRINITY UNIVERSITY invites applications for the position of the Jesse H. Jones Professor of Accounting within the Department of Business Administration, effective August 2009. The position requires a Ph.D., D.B.A., or equivalent degree in Accounting. An established record of research, a commitment to continued scholarship, and excellence in teaching are required. The teaching load is two courses a semester. The Jesse H. Jones Professor will be expected to have an interest in teaching financial accounting theory and regulation. The salary is competitive. Trinity University is a small, private, highly selective, primarily undergraduate institution with a liberal arts and sciences tradition and a commitment to strong programs in selected professional fields. The Department of Business Administration is the largest academic unit on campus in terms of student majors. The Department is accredited by the AACSB and is member of the EFMD. The Department offers bachelor's and master's degrees in accounting. Applicants should send a letter of interest, *curriculum vitae*, and a sample of written work to: Dr. Linda S. Specht, Chair of Search Committee, Department of Business Administration, Trinity University, One Trinity Place, San Antonio, Texas 78212-7200; or Email: lspecht@trinity.edu. Review of applications will begin immediately, and the position will remain open until filled. We encourage applications from women and minorities. The University is an Equal Opportunity Employer.

414 DEPAUL UNIVERSITY invites Professors of Accounting of all ranks at Ph.D.-granting universities to apply for the School of Accountancy and Management Information Systems Ledger & Quill Visiting Professorship. Appointment is for one to two quarters. The Visiting Professor is asked to teach two-three courses in his or her field of specialty, interact on an informal basis with DePaul faculty and deliver a research seminar presentation to the faculty and Ledger & Quill alumni members. Applicants are expected to have an ongoing research agenda and to be effective teachers. In addition to salary, DePaul University and Ledger & Quill Society will provide a housing allowance for the term of appointment and make available additional support as necessary for research. Please address inquiries to: John Ahern, School of Accountancy and MIS, DePaul University, One East Jackson Blvd., Chicago, IL 60604; Phone: (312) 362-6624; or Email: jahern@depaul.edu.

415 DEPAUL UNIVERSITY School of Accountancy and MIS invites applications for a tenure-track position at the Assistant, Associate, or Full-Professor level starting in Fall 2009. Candidates must hold a doctoral degree in Accounting from an AACSB-accredited school. ABDs will be considered if completion of dissertation is anticipated by starting date. Candidates should demonstrate potential for success in scholarly research and excellence in teaching. Qualified individuals in all specialty areas of accounting will be considered. Salary and benefits are competitive with AACSB schools. Review of applications will begin immediately and will continue until the position is filled. Interested applicants should submit *curriculum vita*, samples of scholarly work, teaching evaluations, and two letters of reference to: Phillip Chomiak, Coordinator of Faculty and Curriculum, School of Accountancy and MIS, DePaul University, One East Jackson Blvd., Chicago, IL 60604; Email: pchomiak@depaul.edu. Please submit applications by July 25 if you wish to be considered for an interview at the AAA Annual Meeting in Anaheim, CA. Information about DePaul University can be found at: http://www.depaul.edu. Information about the School of Accountancy and MIS can be found at: http://accountancy.depaul.edu.

416 ILLINOIS STATE UNIVERSITY Department of Accounting invites applications for a full-time, tenure-track Assistant or Associate Professor position. The successful applicant will begin August 16, 2009. Qualifications include a Ph.D. or D.B.A. in Accounting with a strong commitment to quality teaching, research, and service. ABDs will be considered if substantial progress has been made on the dissertation. Preference will be given to applicants with a primary teaching interest in managerial and cost accounting and a secondary interest in international and financial accounting. The normal teaching load is nine credit hours per semester with a reduced load in the first two years. To assure full consideration, please send a letter of application and current *vita* by August 15, 2008 to: Gerry McKean, Interim Chairperson, Illinois State University, Department of Accounting, Campus Box 5520, Normal, IL 61790-5520; Email: gerry.mckean@ilstu.edu.

417 WESTERN WASHINGTON UNIVERSITY invites applications for tenure-track Assistant or Associate Professor position in financial accounting, secondary interest in auditing and/or systems beginning Fall 2009. Doctoral degree in accounting or equivalent required by appointment date. Duties include teaching undergraduate and graduate courses, university service, and scholarly publication. View announcement, including complete list of qualifications, at: http://www.acadweb.wwu.edu/hr/Jobs/faculty.asp. Western overlooks Puget Sound, is situated between Seattle and Vancouver, BC, and has 13,000 students. AACSB-accredited. Please send letter of application, *curriculum vitae*, transcripts, evidence of teaching effectiveness, and names of three references to: Professor George Sanders, Search Committee Chair, Department of Accounting, Western Washington University, Bellingham, WA 98225-9071; Phone: (360) 650-3202; Email: ACCTSearch@wwu.edu. Application review will begin: 9/19/08. AA/EOE.

418 SEATTLE UNIVERSITY, Albers School of Business and Economics, seeks an Assistant/Associate Professor of Accounting. A Ph.D. in Accounting is required. While applications in all areas will be considered, preference will be given to those with experience teaching undergraduate and/or graduate courses in Financial Accounting. Candidates must be committed to excellence in teaching and scholarly research. The Albers School is accredited by the AACSB International. Albers' programs include a strong undergraduate business program, Master of Professional of Accounting, M.B.A., and Leadership Executive M.B.A. program. Interested applicants should send their *vita*, samples of research, teaching evaluations, and three letters of reference to: Dr. Bruce Koch, Chair, Department of Accounting, Seattle University, Seattle, WA 98122; or Email: kochb@seattleu.edu. Seattle University, founded in 1891, continues a 450-year tradition of Jesuit Catholic higher education. The University's Jesuit Catholic ideals underscore its commitment to the centrality of teaching, learning, and scholarship, of values-based education grounded in the Jesuit and Catholic traditions, of service and social justice, of lifelong learning, and of educating the whole person. Located in the heart of dynamic Seattle, the University enrolls approximately 7,500 undergraduate and graduate students in eight colleges and schools. Students enjoy a university ethos characterized by small classes, individualized faculty attention, a strong sense of community, a commitment to diversity, and an outstanding faculty. Seattle University is an Equal Opportunity/Affirmative Action Employer.

419 UNIVERSITY OF CINCINNATI Department of Accounting invites applications for a one-year visiting position beginning in Fall 2008, subject to budgetary approval. Qualifications include a Ph.D. and demonstrated success in teaching a variety of courses in financial and managerial accounting at the undergraduate and graduate levels. The college is AACSB-accredited at the B.B.A. and M.B.A. levels and offers a Ph.D. The department offers M.S. degrees in Accounting and Taxation. Send a *curriculum vitae* to: Jens Stephan, 329 Lindner Hall (ML 211), University of Cincinnati, Cincinnati, OH 45221-0211. The University of Cincinnati is an Affirmative Action/Equal Employment Opportunity Employer.

420 UNIVERSITY OF DELAWARE Chairperson, Department of Accounting and Management Information Systems. Duties: Provide leadership and support for the department faculty; promote an environment conducive to significant scholarly activity. Qualifications: Ph.D. in appropriate discipline. For a complete list of duties and qualifications, please visit our website at: http://www.udel.edu/udjobs/current/faculty. Contact: Send a statement addressing attributes and vision for the department, a current résumé, names and contact information of three references, and any other materials reflective of the applicant's accomplishments to: Search Committee Chair, Dept of Accounting & MIS, Alfred Lerner College of Business & Economics, University of Delaware, Newark, DE 19716; or Email: sjones@udel.edu. All application materials shall be shared with departmental faculty. Review of applications will begin July 1, 2008, and will continue until the position is filled. The University of Delaware is an Equal Opportunity Employer and encourages applications from minority group members and women.

421 UNIVERSITY OF SOUTHERN DENMARK Department of Business and Economics invites applications for a tenured Full Professorship in Accounting. The Full Professorship is a permanent position that carries teaching obligations and research responsibilities in the field of Accounting. The Professor is expected to contribute actively to the development of the department's research and teaching environment, to take on teaching and duties as supervisor at bachelor, master's, and Ph.D. level as well as administrative tasks. Applicants must document strong and original research achievements at an international level, and must have experience in supervision of Ph.D. students. You cannot apply for the position based on this advertisement. You can see the full advertisement on the university's homepage: http://www.jobs.sdu.dk/. Position No. 341/526-085465. The closing date is November 3, 2008 at 12:00pm.

422 EASTERN MICHIGAN UNIVERSITY seeks applicants for a tenure-track Assistant Professor position to begin Fall 2009, subject to availability of funding. Primary interest in accounting information systems, financial, or managerial accounting is desired. A Ph.D. with a major in accounting from an AACSB-accredited school or its equivalent is required; however, an ABD with substantial evidence of completion will be considered. CPA or other professional certifications and teaching experience desired. Salary is competitive. EMU is a public, comprehensive university of 24,000 students in southeastern Michigan and the College of Business is AACSB-accredited. Submit letter, *curriculum vita*, transcripts, teaching evaluations, and three reference letters to: Accounting Faculty Position, EMU Academic Human Resources, 202 Boone Hall, Ypsilanti, MI 48197. Review of applications will start immediately and continue until the positions are filled. For more information, contact Dr. Susan Kattelus at: susan.kattelus@emich.edu; or go to: http://www.accfin.emich.edu. AA/EOE.

423 UNIVERSITY OF NORTH TEXAS invites applications for two or more tenure-track faculty positions effective Fall 2008. Areas of need include: Financial and Taxation. The successful candidate must have an earned doctorate in Accounting by August 2008 and a commitment to excellence in research and teaching. Applications for Assistant, Associate, or Professor will be considered. A national reputation based on record and recent publications in top-quality journals is expected for senior rank candidates. Professional certification is preferred. Salaries are competitive. UNT is a comprehensive university, offering undergraduate, master's, and doctoral programs. The College of Business Administration is accredited by AACSB and the Department of Accounting has separate AACSB accreditation. More information about the department is available at: http://www.coba.unt.edu/acct/. The University of North Texas is an emerging research institution located in the vibrant and rapidly expanding Dallas-Fort Worth metropolitan area and situated in close proximity to DFW International Airport. University enrollment is over 34,000 students with more than 6,500 graduate students. UNT offers 257 undergraduate and graduate majors and concentrations. Review of applications will begin immediately and continue until the positions are filled. Please mail letter of interest and *vita* with references to: Dr. Paul D. Hutchison, Department of Accounting, PO Box 305219, Denton, TX 76203-5219; or Email: naudei@unt.edu. The University of North Texas is an Equal Opportunity/Affirmative Action Employer.

424 SAN JOSE STATE UNIVERSITY invites applications for Fall 2008 for tenure-track positions as Associate or Assistant Professor or temporary appointment as Visiting Professor. Positions are available in Financial/Managerial Accounting/Audit, Audit/Accounting Information Systems, and in Taxation. The position in Taxation is open rank. The candidate must have demonstrated versatility in subject matter competencies and pedagogy. The teaching assignment is at both graduate and undergraduate levels including traditional and accelerated formats. Funding for the positions is pending. The minimum credential requirement is ABD for tenure-track and visiting appointments. Strong preference will be given to candidates who hold a Ph.D. from an AACSB-accredited university. The application deadline is December 31, 2008 or until the position is filled. Send application letter, *vita*, teaching evaluations, and three letters of reference to: Dr. Janis Zaima, Chair, Accounting and Finance Department, College of Business, San Jose State University, One Washington Square, BT850, San Jose, CA 95192-0066; Phone: (408) 924-3490; Email: zaima_j@cob.sjsu.edu. Interviews at AAA may be scheduled with Dr. Zaima. SJSU is an Equal Opportunity/ Affirmative Action Employer committed to the core values of inclusion, civility, and respect for each individual.

425 UTAH STATE UNIVERSITY Assistant, Associate, or Full Professor in Accounting-Tooele Regional Campus. The School of Accountancy in the Jon M. Huntsman School of Business offers a nine-month (academic year) tenure-track position at the rank of Assistant, Associate, or Full Professor in Accounting beginning August 2008 (or until filled). The role requires approximately 70 percent teaching, 20 percent research, and 10 percent service and professional engagement activities. The department has outreach programs within the Utah State University system. As part of USU's mission to make its academic programs accessible throughout the state, this position will be physically located at the USU-Uintah Basin Regional Campus in Vernal, Utah. See: http://jobs.usu.edu (req. ID 051307) for full job description and to apply online. AA/EOE

426 UNIVERSITY OF TENNESSEE AT CHATTANOOGA invites applications for a tenure-track position beginning Fall 2009. Applicants from all areas of emphasis will be considered, with special consideration given to Auditing and Financial Accounting specialists. Candidates should have a Ph.D. or D.B.A. in Accounting or an estimated completion date before August 2009. Candidates must be committed to excellence in teaching; we are especially interested in faculty who want to combine teaching and research with a close working relationship with the Chattanooga community. Salary and benefits are AACSB competitive. If interested, please forward a *vitae* and references to (email is acceptable): Dr. Stan Davis, UT Chattanooga, Dept. 6206, 615 McCallie Avenue, Chattanooga, TN 37403; Phone: (423) 425-4152; Email: stan-davis@utc.edu. Minority applicants are strongly encouraged to apply. The University of Tennessee at Chattanooga is an Equal Employment Opportunity, Affirmative Action, Title VI and IX, Section 504, ADA Institution.

427 NORTHERN ILLINOIS UNIVERSITY invites applications for anticipated tenure-track openings for accountancy faculty at the rank of Assistant or Associate Professor beginning Fall 2009. We are primarily interested in candidates who have a teaching interest in Managerial Accounting, Accounting Information Systems, or Financial Accounting. NIU offers the Bachelor of Science in Accountancy, Master of Accounting Science, and Master of Science in Taxation degrees. Information about our nationally ranked programs can be found at: http://www.cob.niu.edu/accy/. Candidates must be qualified to teach at the undergraduate and graduate levels. Candidates must have, or expect to have, a Ph.D. degree when employment begins. Teaching experience, business experience, and professional certification are desirable. We are particularly interested in faculty who want to combine their research and teaching with a close working relationship with the professional business community. NIU representatives will be available at the AAA Annual Meeting in Anaheim, California (August 3–6, 2008). Applicants must send a cover letter and *curriculum vitae* to: Jim Young, Chair, Department of Accountancy, Northern Illinois University, DeKalb, IL 60115. Complete applications must be received by August 15, 2008. AA/EEO.

428 UNIVERSITY OF SCRANTON Kania School of Management (AACSB) invites applications for its tenure-track position in Accounting Information Systems beginning August 2009, at the rank of Assistant Professor. Duties include teaching at the undergraduate and graduate levels, scholarly research activities meeting AACSB-related criteria, and service. The primary teaching responsibilities will be in the areas of accounting information systems and information systems auditing. The qualifications for the position include an appropriate earned doctorate or ABD progressing toward completion. The University of Scranton is, by tradition and choice, a Catholic and Jesuit university. The University is committed to developing a diverse faculty, staff, and student body and to modeling an inclusive campus community. Applications (including *vita*, transcripts, and teaching evaluations) may be submitted to Dr. Robyn Lawrence at: accounting@scranton.edu. Applications will be considered until the position is filled. The University of Scranton is an EOE/Affirmative Action Employer/Educator. Veterans, minority persons, women, and persons with disabilities are encouraged to apply.

429 UNIVERSITY OF SCRANTON Kania School of Management (AACSB) invites applications for its tenure-track position in Taxation beginning August 2009, at the rank of Assistant Professor. Duties include teaching at the undergraduate and graduate levels, scholarly research activities meeting AACSB-related criteria, and service. The primary teaching responsibilities will be in taxation. The faculty member will also be responsible for administering the University's VITA program. The qualifications for the position include an appropriate earned doctorate or ABD progressing toward completion. The University of Scranton is, by tradition and choice, a Catholic and Jesuit university. The University is committed to developing a diverse faculty, staff, and student body and to modeling an inclusive campus community. Applications (including *vita*, transcripts, and teaching evaluations) may be submitted to Dr. Robyn Lawrence at: accounting@scranton.edu. Applications will be considered until the position is filled. The University of Scranton is an EOE/Affirmative Action Employer/Educator. Veterans, minority persons, women, and persons with disabilities are encouraged to apply.

430 UNIVERSITY OF SCRANTON Kania School of Management (AACSB) invites applications for its tenure-track position in Auditing beginning August 2009, at the rank of Assistant Professor. Duties include teaching at the undergraduate and graduate levels, scholarly research activities meeting AACSB-related criteria, and service. The primary teaching responsibilities will be in the areas of auditing and computer auditing. An ability to integrate auditing with accounting information systems is desirable. The qualifications for the position include an appropriate earned doctorate or ABD progressing toward completion. The University of Scranton is, by tradition and choice, a Catholic and Jesuit university. The University is committed to developing a diverse faculty, staff, and student body and to modeling an inclusive campus community. Applications (including *vita*, transcripts, and teaching evaluations) may be submitted to Dr. Robyn Lawrence at: accounting@scranton.edu. Applications will be considered until the position is filled. The University of Scranton is an EOE/Affirmative Action Employer/Educator. Veterans, minority persons, women, and persons with disabilities are encouraged to apply.

431 VILLANOVA UNIVERSITY Villanova School of Business invites applications for a tenure-track faculty position at the Assistant or Associate Professor level beginning Fall 2009 with a primary need in Financial Accounting. Qualifications include outstanding research potential and excellence in teaching along with a doctorate in Accounting. Villanova University is a Catholic University of the Augustinian tradition located on a picturesque campus in the suburban mainline area of Philadelphia. Undergraduate and other programs are nationally ranked by *BusinessWeek*. Salary, benefits, and support are competitive with AACSB-accredited schools. VSB representatives will be available at the AAA Annual Meeting in Anaheim, CA. Send a cover letter and *vitae* that includes the names of three references to: Search Committee C/O James Bierstaker, Accounting and IS Department, Villanova School of Business, Villanova University, Villanova, PA 19085; or Email: james.bierstaker@villanova.edu. Application materials will be shared with department faculty. Villanova University is an Equal Opportunity Employer and encourages applications from minority group members and women.

432 OKLAHOMA STATE UNIVERSITY School of Accounting in the William S. Spears School of Business, invites applications for several open positions. All ranks and areas of research emphasis will be considered. Applicants must have an appropriate earned doctorate and those at the senior level should have a distinguished ongoing record of scholarship. All applicants must have a commitment to instructional excellence. Positions are located on the OSU/Stillwater (OSU/Tulsa) campus, but could be called upon to occasionally teach on the OSU/Tulsa (OSU/Stillwater) campus. Applicant screening will begin immediately and will continue until the position is filled. For full consideration please submit *vita* by October 15, 2008. Letters of application accompanied by a *curriculum vitae* should be sent to: Professor Don R. Hansen, Head, School of Accounting, Oklahoma State University, 401 Business, Stillwater, OK 74078; Phone: (405) 744-5123; Email: don.hansen@okstate.edu. Oklahoma State University is an Affirmative Action/Equal Opportunity/E-Verify Employer committed to diversity.

433 UNIVERSITY OF BRITISH COLUMBIA—OKANAGAN Faculty of Management (http://web.ubc.ca/okanagan/welcome.html) invites applications for full-time tenure-track positions in Accounting, effective July 1, 2009 at the rank of Assistant Professor. The successful candidates are expected to teach undergraduate courses to a diverse student body, conduct research, and participate actively in the ongoing design and development of our innovative accounting program and of our innovative concentration areas. Candidates should possess a Ph.D. or equivalent degree in Accounting, or be close to completing one and provide demonstrated evidence and commitment to research and teaching. A professional accounting designation is preferred. Under exceptional circumstances, candidates who possess a relevant Master's degree and a professional accounting designation with a minimum of three years of experience in public practice, industry, or the public sector may apply for a faculty position as tenure-track Instructor. Subject to budgetary approval, salary and benefits are competitive and commensurate with qualifications. The search will close on December 1, 2008, or when the positions have been filled. Please send covering letter, *cv*, and the names and contact information of three referees to: Dr. Ian Stuart, Dean, Faculty of Management, UBC Okanagan, 3333 University Way, Kelowna, BC, Canada V1V 1V7; Phone: (250) 807-9656; Fax: (250) 807-8533; Email: ian.stuart@ubc.ca. All qualified candidates are encouraged to apply. UBC hires on the basis of merit and is committed to employment equity. We encourage all qualified persons to apply. However, Canadians and permanent residents of Canada will be given priority.

434 FRANK FARINA position wanted: Attorney/CPA/M.B.A. with extensive professional experience as securities litigator and auditor (external and internal), and four years adjunct teaching experience at two nationally ranked universities in Washington, D.C., seeks full-time faculty position. Teaching/research interests include auditing, accounting, SARBOX, and business law. Also interested in developing cross-discipline continuing education courses for attorneys and accountants. Will consider non-tenure-track or visiting appointments. Available beginning Fall 2008. Please email: Tubalaw@aol.com; or Phone: (610) 240-9820.

435 MORGAN STATE UNIVERSITY Graves School of Business and Management invites applications for one or two tenure-track positions starting August 2009. All ranks will be considered. Candidates should have a Ph.D. degree in accounting from an AACSB-accredited institution and research and teaching interests in financial accounting, managerial accounting, or auditing. Candidates for Professor or Associate Professor should have a significant record of publications in recognized accounting journals. Salaries are AACSB-competitive. The University has business school accreditation and accounting accreditation by the AACSB. The business school offers a B.S. degree in accounting and a Ph.D. degree in Business Administration with Accounting concentration. Master's level accounting courses are offered in the general M.B.A. program. A master's degree program in Accounting is expected to be offered in August 2009. Interested candidates should send academic *vitae* to: Alex P. Tang, Chair, Recruiting Committee, Department of Accounting and Finance, Morgan State University, Baltimore, MD 21251: or Email: Alex.Tang@morgan.edu. We will interview at the 2009 AAA Annual Meeting. Morgan State University is an Affirmative Action/Equal Opportunity Employer.